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(54) FRAUD DETECTION USING PREDICTIVE MODELLING

BETRUGSERFASSUNG MIT VORAUSSAGENDER FORMGEBUNG

SYSTEME DE DETECTION DE FRAUDE FAISANT APPEL A LA MODELISATION PREDICTIVE

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(56) References cited:
EP-A- 0 418 144
EP-A- 0 421 808
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Description

BACKGROUND OF THE INVENTION

1. Field of the Invention

This invention relates generally to the detection of fraudulent use of customer accounts and account numbers, including for example credit card transactions. In particular, the invention relates to an automated fraud detection system and method that uses predictive modeling to perform pattern recognition and classification in order to isolate transactions having high probabilities of fraud.

2. Description of the Related Art

In the following discussion, the term "credit card" will be used for illustrative purposes; however, the techniques and principles discussed herein apply to other types of customer accounts, such as charge cards, bank automated teller machine cards and telephone calling cards.

Credit card issuers conventionally attempt to limit fraud losses by immediately closing a customer's account upon receiving a report that the card has been lost or stolen. Typically, the customer's credit information is then transferred to a new account and a new card is issued. This procedure is only effective in limiting fraudulent use of lost or stolen cards after the loss or theft has been reported to the issuer.

In many cases, however, fraudulent use occurs without the knowledge of the cardholder, and therefore no report is made to the issuer. This may occur if the customer is unaware that the card has been lost or stolen, or if other techniques are employed to perpetrate the fraud, such as: use of counterfeit cards; merchant fraud; application fraud; or interception of credit cards in the mail. In all these situations, the fraudulent use may not be detected until (and unless) the cardholder notices an unfamiliar transaction on his or her next monthly statement and contests the corresponding charge. The concomitant delay in detection of fraud may result in significant losses. User fraud, in which the user claims that a valid transaction is invalid, is also possible.

Issuers of credit cards have sought to limit fraud losses by attempting to detect fraudulent use before the cardholder has reported a lost or stolen card. One conventional technique is known as parameter analysis. A parameter analysis fraud detection scheme makes a decision using a small number of database fields combined in a simple Boolean condition. An example of such a condition is:

if (number of transactions in 24 hours > X) and (more than Y dollars authorized) then flag this account as high risk

Parameter analysis will provide the values of X and Y that satisfy either the required detection rate or the required false positive rate. In a hypothetical example, parameter values of X=400 and Y=1000 might capture 20% of the frauds with a false positive rate of 200:1, while X=6 and Y=2000 might capture 8% of the frauds with a false positive rate of 20:1.

The rules that parameter analysis provides are easily implemented in a database management system, as they are restricted to Boolean (e.g., and, or) combinations of conditions on single variables.

Parameter analysis derives rules by examining the single variables most able to distinguish fraudulent from non-fraudulent behavior. Since only single-variable threshold comparisons are used, complex interactions among variables are not captured. This is a limitation that could cause the system to discriminate poorly between fraudulent and valid account behavior, resulting in low capture rates and high false-positive rates.

Additionally, an effective fraud detection model generally requires more variables than conventional parameter analysis systems can handle. Furthermore, in order to capture new fraud schemes, parameter analysis systems must be redeveloped often, and automated redevelopment is difficult to implement.

One prior art document, WO-A-8906398, describes a device for analyzing a data processing transaction by: extracting only those data usefull for analysis of the trans-action; deleting signals corresponding to the transaction deemed to comply with a set of predetermined rules; filtering to eliminate non-significant variations of the transaction to be analyzed; and classifying signals to one or more classes according to a predetermined criteria. This device is susceptible to applicticn to delivery of payment authorizations to credit card users. Another document, EP-A-0 418 144, describes a method of limiting risks associated with a computerized transaction by comparing the transaction request with predetermined statistical data representative of evaluation of a risk of non-conforming utilization. The statistical data describes the mean number or amount of transactions effected during the course of successive time periods, and is derived by dividing time into consecutive unequal periods whose durations are chosen such that the probability of a transaction being effected or a mean amount being requested during a course of each of the time periods is basically consistent.

It is desirable, therefore, to have an automated system that uses available information regarding cardholders, merchants, and transactions to screen transactions and isolate those which are likely to be fraudulent, and which captures a relatively high proportion of frauds while maintaining a relatively low false-positive rate. Preferably, such a

system should be able to handle a large number of interdependent variables, and should have capability for redevelopment of the underlying system model as new patterns of fraudulent behavior emerge.
Accordingly, the present invention provides a computer-implemented process for identifying and determining fraudulent transaction data according to the features of claim 1 and a computer-controlled transaction processing system according to the features of claim 12.

BRIEF DESCRIPTION OF THE DRAWINGS

Figure 1 is a block diagram of an implementation of the present invention.

Figure 2 is a sample system monitor screen which forms part of a typical output interface for the present invention.

Figure 3 is a sample account selection screen which forms part of a typical output interface for the present invention.

Figure 4 is a sample transaction analysis screen which forms part of a typical output interface for the present invention.

Figure 5 is a sample customer information screen which forms part of a typical output interface for the present invention.

Figure 6 is a sample analyst response screen which forms part of a typical output interface for the present invention.

Figure 7 is a flowchart illustrating the major functions and operation of the present invention.

Figure 8 is a block diagram showing the overall functional architecture of the present invention.

Figure 9 is a diagram of a single processing element within a neural network.

Figure 10 is a diagram illustrating hidden processing elements in a neural network.

Figure 11 is a flowchart of the pre-processing method of the present invention.

Figure 12 is a flowchart of the method of creating a profile record of the present invention.

Figure 13 is a flowchart of the method of updating a profile record of the present invention.

Figure 14 is a flowchart showing operation of a batch transaction processing system according to the present invention.

Figure 15 is a flowchart showing operation of a semi-real-time transaction processing system according to the present invention.

Figure 16 is a flowchart showing operation of a real-time processing system according to the present invention.

Figure 17 is a flowchart showing the overall operation of the transaction processing component of the present invention.

Figure 18 is a flowchart showing the operation of module CSCORE of the present invention.

Figure 19 is a flowchart showing the operation of DeployNet of the present invention.

Figure 20 is a flowchart showing cascaded operation of the present invention.

Figure 21 is a portion of a typical CFG model definition file.

DESCRIPTION OF THE PREFERRED EMBODIMENT

The Figures depict preferred embodiments of the present invention for purposes of illustration only. One skilled in the art will readily recognize from the following discussion that alternative embodiments of the structures and methods illustrated herein may be employed without departing from the principles of the invention described herein.

Referring now to Figure 1, there is shown a block diagram of a typical implementation of a system 100 in accordance with the present invention. Transaction information is applied to system 100 via data network 105, which is connected to a conventional financial data facility 106 collecting transaction information from conventional sources such as human-operated credit-card authorization terminals and automated teller machines (not shown). CPU 101 runs software program instructions, stored in program storage 107, which direct CPU 101 to perform the various functions of the system. In the preferred embodiment, the software program is written in the ANSI C language, which may be run on a variety of conventional hardware platforms. In accordance with the software program instructions, CPU 101 stores the data obtained from data network 105 in data storage 103, and uses RAM 102 in a conventional manner as a workspace. CPU 101, data storage 103, and program storage 107 operate together to provide a neural network model 108 for predicting fraud. After neural network 108 processes the information, as described below, to obtain an indication of the likelihood of fraud, a signal indicative of that likelihood is sent from CPU 101 to output device 104.

In the preferred embodiment, CPU 101 is a Model 3090 IBM mainframe computer, RAM 102 and data storage 103 are conventional RAM, ROM and disk storage devices for the Model 3090 CPU, and output device 104 is a conventional means for either printing results based on the signals generated by neural network 108, or displaying the results on a video screen using a window-based interface system, or sending the results to a database for later access, or sending a signal dependent on the results to an authorization system (not shown) for further processing.

Referring now also to Figures 2 through 6, there are shown sample screens from a conventional window-based interface system (not shown) which forms part of output device 104. Figure 2 shows system monitor 201 that allows

a fraud analyst or system supervisor to review system performance. System monitor 201 shows a cutoff score 202 above which accounts will be flagged, the number of accounts with scores above the cutoff 203, and the fraud score 204 and account number 205 for a particular account.

Figure 3 shows account selection screen 301 that includes a scrolling window 302 allowing the analyst to select high-risk transactions for review, and a set of buttons 303 allowing the analyst to select further operations in connection with the selected transactions.

Figure 4 shows transaction analysis screen 401 that allows the fraud analyst to examine each high-risk transaction and determine appropriate fraud control actions. It includes account information 402, fraud score 403, explanations derived from reason codes 404 that indicate the reasons for fraud score 403, and two scrolling windows 405 and 406 that show transaction information for the current day and the past seven days 405, and for the past six months 406.

Figure 5 shows customer information screen 501 that allows the analyst to access customer information, including account number 502, customer names 503, best time to call 504, phone numbers 505, and address 506. It also provides access to further functions via on-screen buttons 507.

Figure 6 shows analyst response screen 601 that allows the analyst to log actions taken to control fraud. It includes a series of check boxes 602 for logging information, a comment box 603, and on-screen buttons 604 allowing access to other functions.

Referring now also to Figure 7, there is shown an overall flowchart illustrating the major functions and operation of the system 100. First neural network model 108 is trained 701 using data describing past transactions from data network 105. Then data describing the network model are stored 702. Once the model description is stored, system 100 is able to process current transactions. System 100 obtains data for a current transaction 703, and applies the current transaction data to the stored network model 704. The model 108 determines a fraud score and reason codes (described below), which are output 705 to the user, or to a database, or to another system via output device 104.

Referring now to Figure 8, the overall functional architecture of system 100 is shown. System 100 is broken down into two major components: model development component 801 and transaction processing component 802. Model development component 801 uses past data 804 to build neural network 108 containing information representing learned relationships among a number of variables. Together, the learned relationships form a model of the behavior of the variables. Although a neural network is used in the preferred embodiment, any type of predictive modeling technique may be used. For purposes of illustration, the invention is described here in terms of a neural network.

Transaction processing component 802 performs three functions: 1) it determines the likelihood of fraud for each transaction by feeding data from various sources 805, 806 into neural network 108, obtaining results, and outputting them 807; 2) when applicable, it creates a record in a profile database 806 summarizing past transactional patterns of the customer; and 3) when applicable, it updates the appropriate record in profile database 806.

Each of the two components of the system will be described in turn.

Model Development Component 801

Neural Networks: Neural networks employ a technique of "learning" relationships through repeated exposure to data and adjustment of internal weights. They allow rapid model development and automated data analysis. Essentially, such networks represent a statistical modeling technique that is capable of building models from data containing both linear and non-linear relationships. While similar in concept to regression analysis, neural networks are able to capture nonlinearity and interactions among independent variables without pre-specification. In other words, while traditional regression analysis requires that nonlinearities and interactions be detected and specified manually, neural networks perform these tasks automatically. For a more detailed description of neural networks, see D.E. Rumelhart et al, "Learning Representations by Back-Propagating Errors", Nature v. 323, pp. 533-36 (1986), and R. Hecht-Nielsen, "Theory of the Backpropagation Neural Network", in Neural Networks for Perception, pp. 65-93 (1992), the teachings of which are incorporated herein by reference.

Neural networks comprise a number of interconnected neuron-like processing elements that send data to each other along connections. The strengths of the connections among the processing elements are represented by weights. Referring now to Figure 9, there is shown a diagram of a single processing element 901. The processing element receives inputs X_1, X_2,... X_n, either from other processing elements or directly from inputs to the system. It multiplies each of its inputs by a corresponding weight w_1, w_2, ... w_n and adds the results together to form a weighted sum 902. It then applies a transfer function 903 (which is typically non-linear) to the weighted sum, to obtain a value Z known as the state of the element. The state Z is then either passed on to another element along a weighted connection, or provided as an output signal. Collectively, states are used to represent information in the short term, while weights represent long-term information or learning.

Processing elements in a neural network can be grouped into three categories: input processing elements (those which receive input data values); output processing elements (those which produce output values); and hidden processing elements (all others). The purpose of hidden processing elements is to allow the neural network to build intermediate

representations that combine input data in ways that help the model learn the desired mapping with greater accuracy. Referring now to Figure 10, there is shown a diagram illustrating the concept of hidden processing elements. Inputs 1001 are supplied to a layer of input processing elements 1002. The outputs of the input elements are passed to a layer of hidden elements 1003. Typically there are several such layers of hidden elements. Eventually, hidden elements pass outputs to a layer of output elements 1004, and the output elements produce output values 1005.

Neural networks learn from examples by modifying their weights. The "training" process, the general techniques of which are well known in the art, involves the following steps:

1) Repeatedly presenting examples of a particular input/output task to the neural network model;
2) Comparing the model output and desired output to measure error; and
3) Modifying model weights to reduce the error.

This set of steps is repeated until further iteration fails to decrease the error. Then, the network is said to be "trained." Once training is completed, the network can predict outcomes for new data inputs.

Fraud-Related Variables

In the present invention, data used to train the model are drawn from various database files containing historical data on individual transactions, merchants, and customers. These data are preferably pre-processed before being fed into the neural network, resulting in the creation of a set of fraud-related variables that have been empirically determined to form more effective predictors of fraud than the original historical data.

Referring now to Figure 11, there is shown a flowchart of the pre-processing method of the present invention. Individual elements of the flowchart are indicated by designations which correspond to module names.

Data used for pre-processing is taken from three databases which contain past data: 1) past transaction database 1101 (also called an "authorization database") containing two years' worth of past transaction data, which may be implemented in the same data base as past data 804; 2) customer database 1103 containing customer data; and 3) fraud database 1102 which indicates which accounts had fraudulent activity and when the fraudulent activity occurred.

Module readauth.sas 1104 reads transaction data from past transaction database 1101. Module matchauth.sas 1105 samples this transaction data to obtain a new transaction data set containing all of the fraud accounts and a randomly-selected subset of the non-fraud accounts. In creating the new transaction data set, module matchauth.sas 1105 uses information from fraud database 1102 to determine which accounts have fraud and which do not. For effective network training, it has been found preferable to obtain approximately ten non-fraud accounts for every fraud account.

Module readex.sas 1106 reads customer data from customer database 1103. Module matchex.sas 1107 samples this customer data to obtain a new customer data set containing all of the fraud accounts and the same subset of non-fraud accounts as was obtained by module matchauth.sas. In creating the new customer data set, module matchex.sas 1107 uses information from fraud database 1102 to determine which accounts have fraud and which do not.

Module mxmerge.sas 1108 merges all of the data sets obtained by modules matchauth.sas 1105 and matchex.sas 1107. Module genau.sas 1109 subdivides the merged data set into subsets of monthly data.

Module gensamp.sas 1112 samples the data set created by module mxmerge.sas 1108 and subdivided by genau.sas 1109, and creates a new data set called sample.ssd where each record represents a particular account on a particular day with transaction activity. Module gensamp.sas 1112 determines which records are fraudulent using information from fraud database 1102. Module gensamp.sas 1112 provides a subset of authorization days, as follows: From the database of all transactions, a set of active account-days is created by removing multiple transactions for the same customer on the same day. In the set of active account-days, each account day is assigned a "draft number" from 0 to 1. This draft number is assigned as follows: If the account-day is non-fraudulent, then the draft number is set to a random number between 0 and 1. If the account-day is fraudulent and it lies on the first or second day of fraud, then the draft number is set to 0. Otherwise, it is set to 1. Then, the 25,000 account-days with the smallest draft numbers are selected for inclusion in sample.ssd. Thus, all fraudulent account-days (up to 25,000) plus a sample of non-fraudulent account-days are included in sample.ssd.

Module roll15.sas 1113 generates a 15-day rolling window of data. This data has multiple records for each account-day listed in sample.ssd. The current day and 14 preceding days are listed for each sample account.

Module roll15to7.sas 1117 takes the roll15 data set and filters out days eight to 15 to produce roll7, a 7-day rolling window data set 1119. Days eight to 15 are ignored. Module genrolv.sas 1118 generates input variables for a rolling window of the previous 15 days of transactions. It processes a data set with multiple and variable numbers of records per account and produces a data set with one record per account. The result is called rollv.ssd.

Module roll15to1.sas 1114 takes the roll15 data set and filters out days except the current day to produce roll1. Module gencurv.sas 1115 uses roll1 to generate current day variables 1116 describing transactions occurring during the current day.

Module genprof.sas generates profile variables which form the profile records 1111.

Module merge.sas 1120 combines the profile records 1111, 1-day variables 1116, and 7-day variables 1119 and generates new fraud-related variables, as listed below, from the combination. It also merges rollv.ssd with the sample-filtered profile data sets to produce a single data set with both profile and rolling window variables. The result is called the mod1n2 data set 1121 (also called the "training set"), which contains the fraud-related variables needed to train the network. Scaler module 1122 scales the variables such that the mean value for each variable in the scaled training set is 0.0 and the standard deviation is 1.0, to create scaled mod1n2 data set 1123.

Many fraud-related variables may be generated using variations of the pre-processing method described above. Fraud-related variables used in the preferred embodiment include:

- Customer usage pattern profiles representing time-of-day and day-of-week profiles;
- Expiration date for the credit card;
- Dollar amount spent in each SIC (Standard Industrial Classification) merchant group category during the current day;
- Percentage of dollars spent by a customer in each SIC merchant group category during the current day;
- Number of transactions in each SIC merchant group category during the current day;
- Percentage of number of transactions in each SIC merchant group category during the current day;
- Categorization of SIC merchant group categories by fraud rate (high, medium, or low risk);
- Categorization of SIC merchant group categories by customer types (groups of customers that most frequently use certain SIC categories);
- Categorization of geographic regions by fraud rate (high, medium, or low risk);
- Categorization of geographic regions by customer types;
- Mean number of days between transactions;
- Variance of number of days between transactions;
- Mean time between transactions in one day;
- Variance of time between transactions in one day;
- Number of multiple transaction declines at same merchant;
- Number of out-of-state transactions;
- Mean number of transaction declines;
- Year-to-date high balance;
- Transaction amount;
- Transaction date and time;
- Transaction type.

Additional fraud-related variables which may also be considered are listed below:

Current Day Cardholder Fraud Related Variables

bweekend -	current day boolean indicating current datetime considered weekend
cavapvdl -	current day mean dollar amount for an approval
cavapvdl -	current day mean dollar amount for an approval
cavaudl -	current day mean dollars per auth across day
ccoscdom -	current day cosine of the day of month i.e. cos(day ((datepart(cst_dt)* &TWOPI)/30));
ccoscdow -	current day cosine of the day of week i.e. cos(weekday((datepart(cst_dt)* &TWOPI)/7));
ccoscmoy -	current day cosine of the month of year i.e. cos(month ((datepart(cst_dt)* &TWOPI)/12));
cdom -	current day day of month
cdow -	current day day of week
chdzip -	current cardholder zip
chibal -	current day high balance
chidcapv -	current day highest dollar amt on a single cash approve
chidcdec -	current day highest dollar amt on a single cash decline
chidmapv -	current day highest dollar amt on a single merch approve
chidmdec -	current day highest dollar amt on a single merch decline
chidsapv -	current day highest dollar amount on a single approve
chidsau -	current day highest dollar amount on a single auth
chidsdec -	current day highest dollar amount on a single decline
cmoy -	current day month of year
cratdcau -	current day ratio of declines to auths

csincdom - current day sine of the day of month i.e. sin(day ((datepart(cst_dt)* &TWOPI)/30));
csincdow - current day sine of the day of week i.e. sin(weekday((datepart(cst_dt)* &TWOPI)/7));
csincmoy - current day sine of the month of year i.e. sin(month ((datepart(cst_dt)* &TWOPI)/12));
cst_dt - current day cst datetime derived from zip code and CST auth time
ctdapv - current day total dollars of approvals
ctdau - current day total dollars of auths
ctdcsapv - current day total dollars of cash advance approvals
ctdcsdec - current day total dollars of cash advance declines
ctddec - current day total dollars of declines
ctdmrapv - current day total dollars of merchandise approvals
ctdmrdec - current day total dollars of merchandise declines
ctnapv - current day total number of approves
ctnau - current day total number of auths
ctnau10d - current day number of auths in day<=$10
ctnaudy - current day total number of auths in a day
ctncsapv - current day total number of cash advance approvals
ctncsapv - current day total number of cash approves
ctncsdec - current day total number of cash advance declines
ctndec - current day total number of declines
ctnmrapv - current day total number of merchandise approvals
ctnmrdec - current day total number of merchandise declines
ctnsdapv - current day total number of approvals on the same day of week as current day
ctnwdaft - current day total number of weekday afternoon approvals
ctnwdapv - current day total number of weekday approvals
ctnwdeve - current day total number of weekday evening approvals
ctnwdmor - current day total number of weekday morning approvals
ctnwdnit - current day total number of weekday night approvals
ctnweaft - current day total number of weekend afternoon approvals
ctnweapv current day total number of weekend approvals
ctnweeve current day total number of weekend evening approvals
ctnwemor current day total number of weekend morning approvals
ctnwenit current day total number of weekend night approvals
currbal current day current balance
cvrandl current day variance of dollars per auth across day
czrate 1 current day zip risk group 1 'Zip very high fraud rate'
czrate2 current day zip risk group 2 'Zip high fraud rate'
czrate3 current day zip risk group 3 'Zip medium high fraud rate'
czrate4 current day zip risk group 4 'Zip medium fraud rate'
czrate5 current day zip risk group 5 'Zip medium low fraud rate'
czrate6 current day zip risk group 6 'Zip low fraud rate'
czrate7 current day zip risk group 7 'Zip very low fraud rate'
czrate8 current day zip risk group 8 'Zip unknown fraud rate'
ctdsfa01 current day total dollars of transactions in SIC factor group 01
ctdsfa02 current day total dollars of transactions in SIC factor group 02
ctdsfa03 current day total dollars of transactions in SIC factor group 03
ctdsfa04 current day total dollars of transactions in SIC factor group 04
ctdsfa05 current day total dollars of transactions in SIC factor group 05
ctdsfa06 current day total dollars of transactions in SIC factor group 06
ctdsfa07 current day total dollars of transactions in SIC factor group 07
ctdsfa08 current day total dollars of transactions in SIC factor group 08
ctdsfa09 current day total dollars of transactions in SIC factor group 09
ctdsfa10 current day total dollars of transactions in SIC factor group 10
ctdsfa11 current day total dollars of transactions in SIC factor group 11
ctdsra01 current day total dollars of transactions in SIC fraud rate group 01
ctdsra02 current day total dollars of transactions in SIC fraud rate group 02
ctdsra03 current day total dollars of transactions in SIC fraud rate group 03
ctdsra04 current day total dollars of transactions in SIC fraud rate group 04
ctdsra05 current day total dollars of transactions in SIC fraud rate group 05

ctdsra06	current day total dollars of transactions in SIC fraud rate group 06
ctdsra07	current day total dollars of transactions in SIC fraud rate group 07
ctdsva01	current day total dollars in SIC VISA group 01
ctdsva02	current day total dollars in SIC VISA group 02
ctdsva03	current day total dollars in SIC VISA group 03
ctdsva04	current day total dollars in SIC VISA group 04
ctdsva05	current day total dollars in SIC VISA group 05
ctdsva06	current day total dollars in SIC VISA group 06
ctdsva07	current day total dollars in SIC VISA group 07
ctdsva08	current day total dollars in SIC VISA group 08
ctdsva09	current day total dollars in SIC VISA group 09
ctdsva10	current day total dollars in SIC VISA group 10
ctdsva11	current day total dollars in SIC VISA group 11
ctnsfa01	current day total number of transactions in SIC factor group 01
ctnsfa02	current day total number of transactions in SIC factor group 02
ctnsfa03	current day total number of transactions in SIC factor group 03
ctnsfa04	current day total number of transactions in SIC factor group 04
ctnsfa05	current day total number of transactions in SIC factor group 05
ctnsfa06	current day total number of transactions in SIC factor group 06
ctnsfa07	current day total number of transactions in SIC factor group 07
ctnsfa08	current day total number of transactions in SIC factor group 08
ctnsfa09	current day total number of transactions in SIC factor group 09
ctnsfa10	current day total number of transactions in SIC factor group 10
ctnsfa11	current day total number of transactions in SIC factor group 11
ctnsra01	current day total number of transactons in SIC fraud rate group 01
ctnsra02	current day total number of transactons in SIC fraud rate group 02
ctnsra03	current day total number of transactons in SIC fraud rate group 03
ctnsra04	current day total number of transactons in SIC fraud rate group 04
ctnsra05	current day total number of transactons in SIC fraud rate group 05
ctnsra06	current day total number of transactons in SIC fraud rate group 06
ctnsra07	current day total number of transactons in SIC fraud rate group 07
ctnsva01	current day total number in SIC VISA group 01
ctnsva02	current day total number of SIC VISA group 02
ctnsva03	current day total number of SIC VISA group 03
ctnsva04	current day total number of SIC VISA group 04
ctnsva05	current day total number of SIC VISA group 05
ctnsva06	current day total number of SIC VISA group 06
ctnsva07	current day total number of SIC VISA group 07
ctnsva08	current day total number of SIC VISA group 08
ctnsva09	current day total number of SIC VISA group 09
ctnsva10	current day total number of SIC VISA group 10
ctnsva11	current day total number of SIC VISA group 11

7 Day Cardholder Fraud Related Variables

raudymdy	7 day ratio of auth days over number of days in the window
ravapvdl	7 day mean dollar amount for an approval
ravaudl	7 day mean dollars per auth across window
rddapv	7 day mean dollars per day of approvals
rddapv2	7 day mean dollars per day of approvals on days with auths
rddau	7 day mean dollars per day of auths on days with auths
rddauall	7 day mean dollars per day of auths on all days in window
rddcsapv	7 day mean dollars per day of cash approvals
rddcsdec	7 day mean dolalrs per day of cash declines
rdddec	7 day mean dollars per day of declines
rdddec2	7 day mean dollars per day of declines on days with auths
rddmrapv	7 day mean dollars per day of merchandise approvals
rddmrdec	7 day mean dollars per day of merchandise declines

rdnapv	7 day mean number per day of approvals
rdnau	7 day mean number per day of auths on days with auths
rdnauall	7 day mean number per day of auths on all days in window
rdncsapv	7 day mean number per day of cash approvals
rdncsdec	7 day mean number per day of cash declines
rdndec	7 day mean number per day of declines
rdnmrapv	7 day mean number per day of merchandise approvals
rdnmrdec	7 day mean number per day of merchandise declines
rdnsdap2	7 day mean number per day of approvals on same day of week calculated only for those days which had approvals
rdnsdapv	7 day mean number per day of approvals on same day of week as current day
rdnwdaft	7 day mean number per day of weekday afternoon approvals
rdnwdapv	7 day mean number per day of weekday approvals
rdnwdeve	7 day mean number per day of weekday evening approvals
rdnwdmor	7 day mean number per day of weekday morning approvals
rdnwdnit	7 day mean number per day of weekday night approvals
rdnweaft	7 day mean number per day of weekend afternoon approvals
rdnweapv	7 day mean number per day of weekend approvals
rdnweeve	7 day mean number per day of weekend evening approvals
rdnwemor	7 day mean number per day of weekend morning approvals
rdnwenit	7 day mean number per day of weekend night approvals
rhibal	7 day highest window balance
rhidcapv	7 day highest dollar amt on a single cash approve
rhidcdec	7 day highest dollar amt on a single cash decline
rhidmapv	7 day highest dollar amt on a single merch approve
rhidmdec	7 day highest dollar amt on a single merch decline
rhidsapv	7 day highest dollar amount on a single approve
rhidsau	7 day highest dollar amount on a single auth
rhidsdec	7 day highest dollar amount on a single decline
rhidtapv	7 day highest total dollar amount for an approve in a single day
rhidtau	7 day highest total dollar amount for any auth in a single day
rhidtdec	7 day highest total dollar amount for a decline in a single day
rhinapv	7 day highest number of approves in a single day
rhinau	7 day highest number of auths in a single day
rhindec	7 day highest number of declines in a single day
rnaudy	7 day number of days in window with any auths
rnausd	7 day number of same day of week with any auths
rnauwd	7 day number of weekday days in window with any auths
rnauwe	7 day number of weekend days in window with any auths
rncsandy	7 day number of days in window with cash auths
rnmraudy	7 day number of days in window with merchant auths
rtdapv	7 day total dollars of approvals
rtdau	7 day total dollars of auths
rtdcsapv	7 day total dollars of cash advance approvals
rtdcsdec	7 day total dollars of cash advance declines
rtddec	7 day total dollars of declines
rtdmrapv	7 day total dollars of merchandise approvals
rtdmrdec	7 day total dollars of merchandise declines
rtnapv	7 day total number of approvals
rtnapvdy	7 day total number of approves in a day
rtnau	7 day total number of auths
rtnau10d	7 day number of auths in window <=$10
rtncsapv	7 day total number of cash advance approvals
rtncsdec	7 day total number of cash advance declines
rtndec	7 day total number of declines
rtnmrapv	7 day total number of merchandise approvals
rtnmrdec	7 day total number of merchandise declines
rtnsdapv	7 day total number of approvals on the same day of week as current day

rtnwdaft	7 day total number of weekday afternoon approvals
rtnwdapv	7 day total number of weekday approvals
rtnwdeve	7 day total number of weekday evening approvals
rtnwdmor	7 day total number of weekday morning approvals
rtnwdnit	7 day total number of weekday night approvals
rtnweaft	7 day total number of weekend afternoon approvals
rtnweapv	7 day total number of weekend approvals
rtnweeve	7 day total number of weekend evening approvals
rtnwemor	7 day total number of weekend morning approvals
rtnwenit	7 day total number of weekend night approvals
rvraudl	7 day variance of dollars per auth across window

Profile Cardholder Fraud Related Variables

paudymdy -	profile ratio of auth days over number of days in the month
pavapvdl -	profile mean dollar amount for an approval
pavaudl -	profile mean dollars per auth across month
pchdzip -	profile the last zip of the cardholder
pdbm -	profile value of 'date became member' at time of last profile update
pddapv -	profile daily mean dollars of approvals
pddapv2 -	profile daily mean dollars of approvals on days with auths
pddau -	profile daily mean dollars of auths on days with auths
pddau30 -	profile daily mean dollars of auths on all days in month
pddcsapv -	profile daily mean dollars of cash approvals
pddcsdec -	profile daily mean dollars of cash declines
pdddec -	profile daily mean dollars of declines
pdddec2 -	profile daily mean dollars of declines on days with auths
pddmrapv -	profile daily mean dollars of merchandise approvals
pddmrdec -	profile daily mean dollars of merchandise declines
pdnapv -	profile daily mean number of approvals
pdnau -	profile daily mean number of auths on days with auths
pdnau30 -	profile daily mean number of auths on all days in month
pdncsapv -	profile daily mean number of cash approvals
pdncsdec -	profile daily mean number of cash declines
pdndec -	profile daily mean number of declines
pdnmrapv -	profile daily mean number of merchandise approvals
pdnmrdec -	profile daily mean number of merchandise declines
pdnw1ap2 -	profile mean number of approvals on Sundays which had auths
pdnw1apv -	provilde mean number of approvals on Sundays (day 1 of week)
pdnw2ap2 -	profile mean number of approvals on Mondays which had auths
pdnw2apv -	profile mean number of approvals on Mondays (day 2 of week)
pdnw3ap2 -	profile mean number of approvals on Tuesdays which had auths
pdnw3apv -	profile mean number of approvals on Tuesdays (day 3 of week)
pdnw4ap2 -	profile mean number of approvals on Wednesdays which had auths
pdnw4apv -	profile mean number of approvals on Wednesdays (day 4 of week)
pdnw5ap2 -	profile mean number of approvals on Thursdays which had auths
pdnw5apv -	profile mean number of approvals on Thursdays (day 5 of week)
pdnw6ap2 -	profile mean number of approvals on Fridays which had auths
pdnw6apv -	profile mean number of approvals on Fridays (day 6 of week)
pdnw7ap2 -	profile mean number of approvals on Saturdays which had auths
pdnw7apv -	profile mean number of approvals on Saturdays (day 7 of week)
pdnwdaft -	profile daily mean number of weekday afternoon approvals
pdnwdapv -	profile daily mean number of weekday approvals
pdnwdeve -	profile daily mean number of weekday evening approvals
pdnwdmor -	profile daily mean number of weekday morning approvals
pdnwdnit -	profile daily mean number of weekday night approvals
pdnweaft -	profile daily mean number of weekend afternoon approvals
pdnweapv -	profile daily mean number of weekend approvals

pdnweeve - profile daily mean number of weekend evening approvals
pdnwemor - profile daily mean number of weekend morning approvals
pdnwenit - profile daily mean number of weekend night approvals
pexpir - profile expiry date stored in profile; update if curr date>pexpir
phibal - profile highest monthly balance
phidcapv - profile highest dollar amt on a single cash approve in a month
phidcdec - profile highest dollar amt on a single cash decline in a month
phidmapv - profile highest dollar amt on a single merch approve in a month
phidmdec - profile highest dollar amt on a single merch decline in a month
phidsapv - profile highest dollar amount on a single approve in a month
phidsau - profile highest dollar amount on a single auth in a month
phidsdec - profile highest dollar amount on a single decline in a month
phidtapv - profile highest total dollar amount for an approve in a single day
phidtau - profile highest total dollar amount for any auth in a single day
phidtdec - profile highest total dollar amount for a decline in a single day
phinapv - profile highest number of approves in a single day
phinau - profile highest number of auths in a single day
phindec - profile highest number of declines in a single day
pm1avbal - profile average bal. during 1st 10 days of mo.
pm1nauths - profile number of auths in the 1st 10 days of mo.
pm2avbal - profile average bal. during 2nd 10 days of mo.
pm2nauths - profile number of auths in the 2nd 10 days of mo.
pm3avbal - profile average bal. during remaining days
pm3nauths - profile number of auths in the last part of the month.
pmovewt - profile uses last zip to determine recent residence move; pmovewt=2 for a move within the previous calendar month; pmovew
pnaudy - profile number of days with auths
pnauw1 - profile number of Sundays in month with any auths
pnauw2 - profile number of Mondays in month with any auths
pnauw3 - profile number of Tuesdays in month with any auths
pnauw4 - profile number of Wednesdays in month with any auths
pnauw5 - profile numberof Thursdays in month with any auths
pnauw6 - profile number of Fridays in month with any auths
pnauw7 - profile number of Saturdays in month with any auths
pnauwd - profile number of weekday days in month with any auths
pnauwe - profile number of weekend days in month with any auths
pncsaudy - profile number of days in month with cash auths
pnmraudy - profile number of days in month with merchant auths
pnweekday - profile number of weekday days in the month
pnweekend - profile number of weekend days in the month
pratdcau - profile ratio of declines to auths
profage - profile number of months this account has had a profile (up to 6 mo.)
psdaudy - profile standard dev. of # days between transactions in a month
psddau - profile standard dev. of $ per auth in a month
ptdapv - profile total dollars of approvals in a month
ptdau - profile total dollars of auths in a month
ptdaudy - profile total dollars of auths in a day
ptdcsapv - profile total dollars of cash advance approvals in a month
ptdcsdec - profile total dollars of cash advance declines in a month
ptddec - profile total dollars of declines in a month
ptdmrapv - profile total dollars of merchandise approvals in a month
ptdmrdec - profile total dollars of merchandise declines in a month
ptdsfa01 - profile total dollars of transactions in SIC factor group 01
ptdsfa02 - profile total dollars of transactons in SIC factor group 02
ptdsfa03 - profile total dollars of transactions in SIC factor group 03
ptdsfa04 - profile total dollars of transactions in SIC factor group 04
ptdsfa05 - profile total dollars of transactions in SIC factor group 05
ptdsfa06 - profile total dollars of transactions in SIC factor group 06

ptdsfa07 -	profile total dollars of transactions in SIC factor group 07
ptdsfa08 -	profile total dollars of transactions in SIC factor group 08
ptdsfa09 -	profile total dollars of transactions in SIC factor group 09
ptdsfa10 -	profile total dollars of transactions in SIC factor group 10
ptdsfa11 -	profile total dolalrs of transactions in SIC factor group 11
ptdsra01 -	profile total dollars of transactions in SIC fraud rate group 01
ptdsra02 -	profile total dollars of transactions in SIC fraud rate group 02
ptdsra03 -	profile total dollars of transactions in SIC fraud rate group 03
ptdsra04 -	profile total dollars of transactions in SIC fraud rate group 04
ptdsra05 -	profile total dollars of transactions in SIC fraud rate group 05
ptdsra06 -	profile total dollars of transactions in SIC fraud rate group 06
ptdsra07 -	profile total dollars of transactions in SIC fraud rate group 07
ptdsva01 -	profile total dollars in SIC VISA group 01
ptdsva02 -	profile total dollars in SIC VISA group 02
ptdsva03 -	profile total dollars in SIC VISA group 03
ptdsva04 -	profile total dollars in SIC VISA group 04
ptdsva05 -	profile total dollars in SIC VISA group 05
ptdsva06 -	profile total dollars in SIC VISA group 06
ptdsva07 -	profile total dollars in SIC VISA group 07
ptdsva08 -	profile total dollars in SIC VISA group 08
ptdsva09 -	profile total dollars in SIC VISA group 09
ptdsva10 -	profile total dollars in SIC VISA group 10
ptdsva11 -	profile total dollars in SIC VISA group 11
ptnapv -	profile total number of approvals in a month
ptnapvdy -	profile total number of approves a day
ptnau -	profile total number of auths in a month
ptnau10d -	profile number of auths in month<=$10
ptnaudy -	profile total number of auths in a day
ptncsapv -	profile total number of cash advance approvals in a month
ptncsdec -	profile total number of cash advance declines in a month
ptndec -	profile total number of declines in a month
ptndecdy -	profile total number of declines in a day
ptnmrapv -	profile total number of merchandise approvals in a month
ptnmrdec -	profile total number of merchandize declines in a month
ptnsfa01 -	profile total number of transactions in SIC factor group 01
ptnsfa01 -	profile total number of transactions in SIC factor group 02
ptnsfa03 -	profile total number of transactions in SIC factor group 03
ptnsfa04 -	profile total number of transactions in SIC factor group 04
ptnsfa05 -	profile total number of transactions in SIC factor group 05
ptnsfa06 -	profile total number of transactions in SIC factor group 06
ptnsfa07 -	profile total number of transactions in SIC factor group 07
ptnsfa08 -	profile total number of transactions in SIC factor group 08
ptnsfa09 -	profile total number of transactions in SIC factor group 09
ptnsfa10 -	profile total number of transactions in SIC factor group 10
ptnsfa11 -	profile total number of transactions in SIC factor group 11
ptnsra01 -	profile total number of transactions in SIC fraud rate group 01
ptnsra02 -	profile total number of transactions in SIC fraud rate group 02
ptnsra03 -	profile total number of transactions in SIC fraud rate group 03
ptnsra04 -	profile total number of transactions in SIC fraud rate group 04
ptnsra05 -	profile total number of transactions in SIC fraud rate group 05
ptnsra06 -	profile total number of transactions in SIC fraud rate group 06
ptnsra07 -	profile total number of transactions in SIC fraud rate group 07
ptnsva01 -	profile total number in SIC VISA group 01
ptnsva02 -	profile total number in SIC VISA group 02
ptnsva03 -	profile total number in SIC VISA group 03
ptnsva04 -	profile total number in SIC VISA group 04
ptnsva05 -	profile total number in SIC VISA group 05
ptnsva06 -	profile total number in SIC VISA group 06

ptnsva07 -	profile total number in SIC VISA group 07
ptnsva08 -	profile total number in SIC VISA group 08
ptnsva09 -	profile total number in SIC VISA group 09
ptnsva10 -	profile total number in SIC VISA group 10
ptnsva11 -	profile total number in SIC VISA group 11
ptnw1ap -	profile total number of approvals on Sundays (day 1 of week)
ptnw2apv -	profile total number of approvals on Mondays (day 2 of week)
ptnw3apv -	profile total number of approvals on Tuesdays (day 3 of week)
ptnw4apv -	profile total number of approvals on Wednesdays (day 4 of week)
ptnw5apv -	profile total number of approvals on Thursdays (day 5 of week)
ptnw6apv -	profile total number of approvals on Fridays (day 6 of week)
ptnw7apv -	profile total number of approvals on Saturdays (day 7 of week)
ptnwdaft -	profile total number of weekday afternoon approvals in a month
ptnwdapv -	profile total number of weekday approvals in a month
ptnwdeve -	profile total number of weekday evening approvals in a month
ptnwdmor -	profile total number of weekday morning approvals in a month
ptnwdnit -	profile total number of weekday night approvals in a month
ptnweaft -	profile total number of weekend afternoon approvals in a month
ptnweapv -	profile total number of weekend approvals in a month
ptnweeve -	profile total number of weekend evening approvals in a month
ptnwemor -	profile total number of weekend morning approvals in a month
ptnwenit -	profile total number of weekend night approvals in a month
pvdaybtwn -	profile variance in number of days between trx's (min of 3 trx)
pvraudl -	profile variance of dollars per auth across month

MERCHANT FRAUD VARIABLES

mtotturn	Merchant Total turnover for this specific merchant
msicturn	Merchant Cumulative SIC code turnover
mctrtage	Merchant Contract age for specific merchant
maagsic	Merchant Average contract age for this SIC code
mavgnbtc	Merchant Average number of transactions in a batch
maamttrx	Merchant Average amount per transaction (average amount per authorization)
mvaramt	Merchant Variance of amount per transaction
mavgtbtc	Merchant Average time between batches
mavgtaut	Merchant Average time between authorizations for this merchant
mratks	Merchant Ratio of keyed versus swiped transactions
mnidclac	Merchant Number of identical customer accounts
mnidcham	Merchant Number of identical charge amounts
mtrxsrc	Merchant What is the source of transaction (ATM, merchant, etc.)
mtrxtrsp	Merchant How is the transaction transported to the source (terminal, non-terminal, voice authorization)
mfloor	Merchant Floor limit
mchgbks	Merchant Charge-backs received
mrtrvs	Merchant Retrievals received (per SIC, merchant, etc.). The issuer pays for a retrieval.
macqrat	Merchant Acquirer risk management rate (in Europe one merchant can have multiple acquirers, but they dont have records about how many or who.)
mprevrsk	Merchant Previous risk management at this merchant? Yes or No
mtyprsk	Merchant Type of previous risk management (counterfeit, multiple imprint, lost/stolen/not received)
msicrat	Merchant SIC risk management rate
mpctaut	Merchant Percent of transactions authorized

Network Training: Once pre-processing is complete, the fraud-related variables are fed to the network and the network is trained. The preferred embodiment uses a modeling technique known as a "feed forward" neural network. This type of network estimates parameters which define relationships among variables using a training method. The preferred training method, well known to those skilled in the art, is called "backpropagation gradient descent optimization", although other well-known neural network training techniques may also be used.

One problem with neural networks built with conventional backpropagation methods is insufficient generalizability. Generalizability is a measure of the predictive value of a neural network. The attempt to maximize generalizability can

be interpreted as choosing a network model with enough complexity so as not to underfit the data but not too much complexity so as to overfit the data. One measure of the complexity of a network is the number of hidden processing elements, so that the effort to maximize generalizability translates into a selection among models having different numbers of hidden processing elements. Unfortunately, it is often not possible to obtain all the nonlinearity required for a problem by adding hidden processing elements without introducing excess complexity. Many weights that come with the addition of each new hidden processing element may not be required or even helpful for the modeling task at hand. These excess weights tend to make the network fit the idiosyncrasies or "noise" of the data and thus fail to generalize well to new cases. This problem, known as overfitting, typically arises because of an excess of weights.

Weight decay is a method of developing a neural network that minimizes overfitting without sacrificing the predictive power of the model. This method initially provides the network with all the nonlinearity it needs by providing a large number of hidden processing elements. Subsequently, it decays all the weights to varying degrees so that only the weights that are necessary for the approximation task remain. Two central premises are employed: 1) when given two models of equivalent performance on a training data set, favor the smaller model; and 2) implement a cost function that penalizes complexity as part of the backpropagation algorithm. The network is trained by minimizing this cost function. Complexity is only justified as it expresses information contained in the data. A weight set that embodies all or almost all of the information in the data and none of the noise will maximize generalizability and performance.

The cost function is constructed by introducing a "decay term" to the usual error function used to train the network. It is designed to optimize the model so that the network captures all the important information in the training set, but does not adapt to noise or random characteristics of the training set. In view of these requirements, the cost function must take into account not only prediction error, but also the significance of model weights. A combination of these two terms yields an objective function which, when minimized, generalizes optimally. Performing a conventional gradient descent with this objective function optimizes the model.

In introducing the decay term, an assumption is made about what constitutes information. The goal is to choose a decay term that accurately hypothesizes the prior distribution of the weights. In finding a good prior distribution, one examines the likelihood that the weights will have a given distribution without knowledge of the data.

Weigend et al, "Generalization by Weight-Elimination with Application to Forecasting", in Advances in Neural Information Processing Systems 3, pp. 875-82, and incorporated herein by reference, discloses the following cost function for weight decay:

$$\frac{1}{2}\sum_{k\in D}(target_k - output_k)^2 + \lambda\sum_{i\in W}\frac{\omega_i^2/\omega_o^2}{1+\omega_i^2/\omega_o^2} \qquad \text{(Eq. 1)}$$

where:

- *D* is the data set;
- $target_k$ is the target, or desired, value for element *k* of the data set;
- $output_k$ is the network output for element *k* of the data set;
- *l* represents the relative importance of the complexity term;
- *W* is the weight set;
- w_i is the value of weight *i*; and
- w_o is a constant that controls the shape of the curve that penalizes the weights.

The first term of the Weigend function measures the performance of the network, while the second term measures the complexity of the network in terms of its size. With this cost function, small weights decay rapidly, while large weights decay slowly or not at all.

A major failing of the Weigend cost function, and similar weight decay schemes, is that they do not accurately mimic the intended prior distribution. Finding a good prior distribution (or "prior") is a key element to developing an effective model. Most of the priors in the literature are sufficient to demonstrate the concept of weight decay but lack the strengths required to accommodate a wide range of problems. This occurs because the priors tend to decay weights evenly for a given processing element, without sufficiently distinguishing important weights (which contain more information) from unimportant weights (which contain less information). This often results either in 1) undesired decaying of important weights, which diminishes the power of the system to accommodate nonlinearity, or 2) undesired retention of excess unimportant weights, which leads to overfitting.

The present invention uses the following improved cost function, which addresses the above problems:

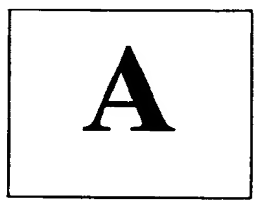
$$\frac{1}{2}\sum_{k\in D}(target_k - output_k)^2 + gl\sum_{i\in W}(c_1 w_i^2 - \frac{1}{1+|w_i|}) \qquad \text{(Eq. 2)}$$

where g represents a new term known as the interlayer gain multiplier for the decay rate, and c_1 is a constant. The interlayer gain multiplier takes into account the relative proximity of the weights to the input and output ends of the network. Thus, the interlayer gain multiplier allows application of the decay term with greater potency to elements that are closer to the inputs, where the majority of the weights typically reside, while avoiding excessive decay on weights corresponding to elements closer to the outputs, which are more critical, since their elimination can effectively sever large numbers of input-side weights.

By intensifying decay on input-side elements, the cost function of Equation 2 improves the ability of model development component 801 to decay individual weights while preserving processing elements containing valuable information. The result is that weak interactions are eliminated while valid interactions are retained. By retaining as many processing elements as possible, the model does not lose the power to model nonlinearities, yet the overfitting problem is reduced because unnecessary individual weights are removed.

Once the cost function has been iteratively applied to the network, weights that have been decayed to a very small number (defined as e) are removed from the network. This step, known as "thresholding the net" is performed because it is often difficult to completely decay weights to zero.

Once the network has been trained using past data, the network's model definition is stored in data files. One portion of this definition, called the "CFG" file, specifies the parameters for the network's input variables, including such information as, for example, the lengths of the variables, their types, and their ranges. Referring now to Figure 21, there is shown a portion of a typical CFG file, specifying parameters for an ACCOUNT variable 2101 (representing a customer account number) and a PAUDYMDY variable 2102 (a profile variable representing the ratio of transaction days divided by the number of days in the month). The file formats used to store the other model definition files for the network are shown below.



ASCII File Formats

The ASCII network data files (*.cta, .sta, .lca, .wta*) consist of tokens (non-whitespace) separated by whitespace (space, tab, newline).
Whitespace is ignored except to separate tokens. Use of line breaks and tabs is encouraged for clarity, but otherwise irrelevant.

File format notation is as follows:

* Bracketed text denotes a token.
* Nonbracketed text denotes a literal token which must be matched exactly, including case.
* Comments on the right are <u>not</u> part of the file format; they simply provide further description of the format.
* In the comments, vertical lines denote a block which can be repeated. Nested vertical lines denote repeatable sub-blocks.

.cta Format

File format	Comments
cts	

(continued)

File format	Comments
<NetName> <Value>	I Repeated as needed

cts and <NetName> must appear first. <NetName> is the standard abbreviation, lowercase (e.g., mbpn). The <Value>s are the network constants values, in the order defined within the constants structure. If a constants value is an array or structured type, each element or field must be a separate token, appearing in the proper order.

Example	Comments
cts	
mbpn	
2	InputSize
1	OutputSize
1	cHidSlabs
2	HiddenSize[0]
0	HiddenSize[1]
0	HiddenSize[2]
3	RandomSeed
1.0	InitWeightMax
0	WtsUpdateFlag
0	ConnectInputs
0	FnClass
1.0	Parm1
1.0	Parm2
-1.0	Parm3
0.0	Parm4
0.0	Parm5
1	cEntTbl
0.0	xLow
0.1	xHigh
0.2	HiddenAlpha[0]
0.0	HiddenAlpha[1]

Example	Comments
0.0	HiddenAlpha[2]
0.1	OutputAlpha
0.9	HiddenBeta[0]
0.0	HiddenBeta[1]
0.0	HiddenBeta[2]
0.9	OutputBeta
0.0	Tolerance
0	WtsUpdateFlag
0	BatchSize
0	LinearOutput
0	ActTblFlag
1	StatsFlag
1	LearnFlag

In this example, HiddenSize, HiddenAlpha, and HiddenBeta are all arrays, so each element (0, 1, 2) has a separate

token, in the order they appear in the type.

.sta Format

File format	Comments
sts <NetName> <cSlab> <nSlab> <cPe> <state>	 I Repeated cSlab times I I I Repeated cPe times

sts and <NetName> must appear first. <NetName>is the standard abbreviation, lowercase. <cSlab> a count of the slabs which have states stored in the file. The remainder of the file consists of cSlab blocks, each describing the states of one slab. The order of the slab blocks in the file is not important. <nSlab> is the slab number, as defined in the *xxx.h* file. cPe is the number of states for the slab. <state> is the value of a single state. If the state type is an array or structured type, each element or field must be a separate token, appearing in the proper order. There should be cPe <state> values in the slab block.

Example	Comments
sts	
mbpn	
6	cSlab
0	nSlab -- SlabInMbpn
2	cPeIn
0.0	StsIn[0]
0.0	StsIn[1]
1	nSlab -- SlabTrnMbpn
1	cPeTrn
0.0	StsTrn[0]
2	nSlab -- SlabHid0Mbpn
2	cPeHid0
0.0	StsHid0[0]
0.0	StsHid0[1]
5	nSlab -- SlabOutMbpn
1	cPeOut
0.0	StsOut[0]
6	nSlab -- SlabBiasMbpn
1	cPeBias
1.0	StsBias[0]
7	nSlab -- SlabStatMbpn
3	cPeStat
0.0	StsStat[0]
0.0	StsStat[1]
0.0	StsStat[2]

.lca Format

File format	Comments
lcl	

(continued)

File format	Comments
<NetName>	
<cSlab>	
<nSlab>	I Repeated cSlab times
<cPe>	I
<local>	II Repeated cPe times

The *.lca* format is just like the *.sta* format except that sts is replaced by lcl. lcl and <NetName> must appear first. <NetName> is the standard abbreviation, lowercase. <cSlab> a count of the slabs which have local data stored in the file. The remainder of the file consists of cSlab blocks, each describing the local data values of one slab. <nSlab> the slab number, as defined in the *xxx.h* file. The order of the slab blocks in the file is not important. cPe is the number of local data values for the slab. <local> is the value of a single local data element. If the local data type is an array or structured type, each element or field must be a separate token, appearing in the proper order. There should be cPe <local> values in the slab block.

Example	Comments
lcl	
mbpn	
3	cSlab
2	nSlab -- SlabHid0Mbpn
2	cPe
0.0	LclHid0[0].Error
0.0	LclHid0[0].NetInp
0.0	LclHid0[1].Error
0.0	LclHid0[1].NetInp
5	nSlab -- SlabOutMbpn
1	cPe
0.0	LclOut[0].Error
0.0	LclOut[0].NetInp
7	nSlab -- SlabStatMbpn
3	cPe
0	LclStat[0].cIter
0.0	LclStat[0].Sum
0	LclStat[1].cIter
0.0	LclStat[1].Sum
0	LclStat[2].cIter
0.0	LclStat[2].Sum

In this example, the <local> values are all structured types, so each field (Error and NetInp; cIter and Sum) has a separate token, in the order they appear in the type.

.wta Format

File format	Comments
wts	
<NetName>	
<cClass>	
<nSlab>	I Repeated cClass times
<nClass>	I
<clcn>	I

(continued)

File format	Comments
<weight>	I I Repeated clcn times

wts and <NetName> must appear first. <NetName> is the standard abbreviation, lowercase. <cClass> is a count of the slab/class combinations which have weights stored in the file. The remainder of the file consists of cClass blocks, each describing the weights of one slab. The order of the class blocks in the file is not important. <nSlab> is the slab number, as defined in the *xxx.h* file. <nClass> is the class number, as defined in the *xxx.h* file. <weight> is the value of a single weight. If the weight type is an array or structured type, each element or field must be a separate token, appearing in the proper order. There should be clcn <weight> values in the slab block.

Example	Comments
wts	
mbpn	
2	cClass
2	nSlab -- SlabHid0Mbpn
0	nClass -- PeHid0MbpnFromPrev
6	clcn
0.0	WtsHid0[PE_0][0]
0.0	WtsHid0[PE_0][1]
0.0	WtsHid0[PE_0][2]
0.0	WtsHid0[PE_1][0]
0.0	WtsHid0[PE_1][1]
0.0	WtsHid0[PE_1][2]
5	nSlab -- SlabOutMbpn
0	nClass -- PeOutMbpnFromPrev
3	clcn
0.0	WtsOut[PE_0][0]
0.0	WtsOut[PE_0][1]
0.0	WtsOut[PE_0][2]

Weights values for a slab and class are stored as a one-dimensional array, but conceptually are indexed by two values -- PE and interconnect within PE. The values are stored in row-major order, as exemplified here.

Transaction Processing Component 802

Once the model has been created, trained, and stored, fraud detection may begin. Transaction processing component 802 of system 100 preferably runs within the context of a conventional authorization or posting system for customer transactions. Transaction processing component 802 reads current transaction data and customer data from databases 805, 806, and generates as output fraud scores representing the likelihood of fraud for each transaction. Furthermore, transaction processing component 802 can compare the likelihood of fraud with a predetermined threshold value, and flag transactions for which the threshold is exceeded.

The current transaction data from database 805 typically includes information such as: transaction dollar amount; date; time (and time zone if necessary); approve/decline code; cash/merchandise code; available credit (or balance); credit line; merchant category code; merchant ZIP code; and PIN verification (if applicable).

The customer data from database 806 typically includes information from three sources: 1) general information on the customer; 2) data on all approved or declined transactions in the previous seven days; and 3) a profile record which contains data describing the customer's transactional pattern over the last six months. The general information on the customer typically includes information such as: customer ZIP code; account open date; and expiration date. The profile record is a single record in a profile database summarizing the customer's transactional pattern in terms of

moving averages. The profile record is updated periodically (usually monthly) with all of the transactions from the period for the customer, as described below.

System 100 can operate as either a batch, semi-real-time, or real-time system. The structure and processing flow of each of these variations will now be described.

Batch System: Figure 14 shows operation of a batch system. Transactions are recorded throughout the day or other convenient period 1402. At the end of the day, the system performs steps 1403 to 1409 for each transaction. It obtains data describing the current transaction 1403, as well as past transaction data, customer data, and profile data 1404. It then applies this data to the neural network 1405 and obtains a fraud score 1406. If the fraud score exceeds a threshold 1407, the account is flagged 1408. In the batch system, therefore, the transaction which yielded the high fraud score cannot itself be blocked; rather, the account is flagged 1404 at the end of the day so that no future transactions are possible. Although the batch system does not permit immediate detection of fraudulent transactions, response-time constraints may mandate use of the batch system in some implementations.

Semi-Real-Time System: The semi-real-time system operates in a similar manner to the batch system and uses the same data files, but it ensures that no more than one high-scoring transaction is authorized before flagging the account. In this system, as shown in Figure 15, fraud likelihood determination is performed (steps 1504 to 1509) immediately after the transaction is authorized 1503. Steps 1504 to 1509 correspond to steps 1403 to 1409 of the batch system illustrated in Figure 14. If the likelihood of fraud is high, the account is flagged 1509 so that no future transactions are possible. Thus, as in the batch system, the current trans-action cannot be blocked; however, the semi-real-time system allows subsequent transactions to be blocked.

Real-Time System: The real-time system performs fraud likelihood determination before a transaction is authorized. Because of response-time constraints, it is preferable to minimize the number of database access calls when using the real-time system. Thus, in this embodiment, all of the customer information, including general information and past transaction data, is found in a single record of profile database 806. Profile database 806 is generated from past transaction and customer data before the transaction processing component starts operating, and is updated after each transaction, as described below. Because all needed data are located in one place, the system is able to retrieve the data more quickly than in the batch or semi-real-time schemes. In order to keep the profile database 806 current, profile records are updated, using moving averages where applicable, after each transaction.

Referring now to Figure 16, there is shown a flowchart of a real-time system using the profile database. Upon receiving a merchant's request for authorization on a transaction 1602, the system obtains data for the current transaction 1603, as well as profile data summarizing transactional patterns for the customer 1604. It then applies this data to the stored neural network model 1605. A fraud score (representing the likelihood of fraud for the transaction) is obtained 1606 and compared to a threshold value 1607. Steps 1601 through 1607 occur before a transaction is authorized, so that the fraud score can be sent to an authorization system 1608 and the transaction blocked by the authorization system if the threshold has been exceeded. If the threshold is not exceeded, the low fraud score is sent to the authorization system 1609. The system then updates customer profile database 806 with the new transaction data 1610. Thus, in this system, profile database 806 is always up to date (unlike the batch and semi-real-time systems, in which profile database 806 is updated only periodically).

Referring now to Figure 12, there is shown the method of creating a profile record. The system performs the steps of this method when there is no existing profile record for the customer. The system reads the past transaction database 1101 for the past six months and the customer database 1103 (steps 1202 and 1203 respectively). It generates a new profile record 1204 with the obtained data and saves it in the profile database 1205. If there are more accounts to be processed 1206, it repeats steps 1202 through 1205.

Referring now to Figure 13, there is shown the method of updating an existing profile record. The system reads the past transaction database 1101 for the past six months, customer database 1103 and profile database (steps 1302, 1303, and 1304 respectively). It combines the data into a single value for each variable in the profile database. This value is generated using one of two formulas.

For variables that represent average values over a period of time (for example, mean dollars of transactions in a month), Equation 3 is used:

$$\text{newProfData} = ((1 - a) * \text{oldProfData}) + (a * \text{currentVal})) \qquad \text{(Eq. 3)}$$

For variables that represent extreme values over a period of time (for example, highest monthly balance), Equation 4 is used:

$$\text{newProfData} = \max(\text{currentVal}, b * \text{oldProfData}) \qquad \text{(Eq. 4)}$$

In Equations 3 and 4:

newProfData is the new value for the profile variable;
oldProfData is the old value for the profile variable;
currentVal is the most recent value of the variable, from the past transaction database; and
a and b are decay factors which are used to give more importance to recent months and less importance to months further in the past.

The value of b is set so that older data will "decay" at an acceptable rate. A typical value for b is 0.95.

The value of a is generated as follows: For the batch and semi-real-time systems, a is set to a value such that the contribution of the value from more than six months previous is nearly zero. For profiles that have been in existence for at least six months, the value of a is 1/6. For newer profiles, the value is 1/(n+1), where n is the number of months since the profile was created. For the real-time system, profile updates do not occur at regular intervals. Therefore, a is determined using the following equation:

$$a = 1 - \exp(-t/T) \qquad \text{(Eq. 5)}$$

where:

t is the time between the current transaction and the last transaction; and
T is a time constant for the specific variable.

Furthermore, for the real-time system, currentVal represents the value of the variable estimated solely using information related to the current transaction and the time since the last transaction, without reference to any other historical information.

Once the new values for the profile variables have been generated, they are placed in an updated profile record 1305 and saved in the profile database 1306. If there are more accounts to be processed 1307, the system repeats steps 1302 through 1306.

In all of these embodiments, the current transaction data and the customer data are preferably pre-processed to derive fraud-related variables which have been empirically determined to be effective predictors of fraud. This is done using the same technique and the same fraud-related variables as described above in connection with neural network training.

Referring now to Figures 17 through 19, there are shown flowcharts illustrating the operation of the preferred embodiment of the transaction processing component. Some of the individual elements of the flowchart are indicated by designations which correspond to module names.

Referring now to Figure 17, there is shown the overall operation of transaction processing component 802. First the system runs module CINITNET 1702, which initializes network structures. Then, it runs module CSCORE 1703. Module CSCORE 1703 uses current trans-action data, data describing transactions over the past seven days, a profile record, and customer data to generate a fraud score indicating the likelihood that the current transaction is fraudulent, as well as reason codes (described below). The system then checks to see whether there are more transactions to be processed 1704, and repeats module CSCORE 1703 for any additional transactions. When there are no more to be processed, the system runs module FREENET 1705, which frees the network structures to allow them to be used for further processing.

Referring now to Figure 18, there is shown the operation of module CSCORE 1703. First, module CSCORE 1703 obtains current transaction data, data describing transactions of the past seven days, the profile record, and customer data (steps 1802 through 1805). From these data, module CSCORE 1703 generates the fraud-related variables 1806 described above. Then, it runs module DeployNet 1807, which applies the fraud-related variables to the stored neural network and provides a fraud score and reason codes. CSCORE then outputs the score and reason codes 1808.

Referring now to Figure 19, there is shown the operation of module DeployNet 1807. Module DeployNet 1807 first scales the fraud-related variables 1902 to match the scaling previously performed in model development. If the value of a variable is missing, DeployNet sets the value to equal the mean value found in the training set. Then it applies the scaled variables to the input layer of neural network 108, in step 1903. In step 1904, it processes the applied data through the network to generate the fraud score. The method of iterating the network is well known in the art.

In addition to providing fraud scores, in step 1904, module DeployNet 1807 optionally generates "reason codes". These codes indicate which inputs to the model are most important in determining the fraud score for a given transaction. Any technique that can track such reasons may be used.

The following module descriptions summarize the functions performed by the individual modules.

FALCON C FILES	
FILE NAME	CINITNET
DESCRIPTION	Contains code to allocate and initialize the network structures.
FUNCTION NAME	CINITNET()
DESCRIPTION	Allocate and initialize the network structures.
FILE NAME	CSCORE
DESCRIPTION	Generates fraud related variables and iterates the neural network.
FUNCTION NAME	SCORE()
DESCRIPTION	Creates fraud related variables from raw variables and makes calls to initialize the input layer and iterate the neural network.
FUNCTION NAME	setInput()
DESCRIPTION	Sets the input value for a processing element in the input layer.
FUNCTION NAME	hiReason()
DESCRIPTION	Finds the three highest reasons for the score.
FILE NAME	CFREENET
DESCRIPTION	Makes function calls to free the network structures.
FUNCTION NAME	CFREENET()
DESCRIPTION	Frees the network structures.
FILE NAME	CCREATEP
DESCRIPTION	Contains the cardholder profile creation code.
FUNCTION NAME	createpf()
DESCRIPTION	Creates a profile record for a cardholder using the previous month's authorizations and cardholder data.
FILE NAME	CUPDATEP
DESCRIPTION	Updates a profile of individual cardholder activity.
FUNCTION NAME	updatepf()
DESCRIPTION	Updates a profile record for a cardholder using the previous profile record values as well as the previous month's authorizations and cardholder data.
FILE NAME	CCOMMON
DESCRIPTION	This file contains functions which are needed by at least two of the following: createpf(), updatepf(), score().
FUNCTION NAME	accumMiscCnts()
DESCRIPTION	Increments counters of various types for each authorization found.
FUNCTION NAME	accumSicCnts()
DESCRIPTION	Increments SIC variable counters.
FUNCTION NAME	initSicCounts()
DESCRIPTION	Initializes the SIC variable counters.
FUNCTION NAME	updateSicMovAvgs()

(continued)

FALCON C FILES	
DESCRIPTION	Updates the SIC profile variables.
FUNCTION NAME	writeMiscToProfile()
DESCRIPTION	Writes various variables to the profile record after they have been calculated.
FUNCTION NAME	hncDate()
DESCRIPTION	Converts a Julian date to a date indicating the number of days since Jan. 1, 1990.
FUNCTION NAME	missStr()
DESCRIPTION	Checks for "missing" flag (a period) in a null terminated string. String must have only blanks and a period to qualify as missing. A string with only blanks will also qualify as "missing".

Cascaded Operation

One way to improve system performance is via "cascaded" operation. In cascaded operation, more than one neural network model is used. The second neural network model is trained by model development component 801 in a similar manner to that described earlier. However, in training the second model, model development component 801 uses only those transactions that have fraud scores, as determined by prior application to the first neural network model, above a predetermined cascade threshold. Thus, the second model provides more accurate scores for high-scoring transactions. While the same fraud-related variables are available to train both models, it is often the case that different variables are found to be significant in the two models.

Referring now to Figure 20, there is shown a flowchart of the operation of the transaction processing component in a cascaded system. First, transaction processing component 802 scores each transaction using the first model 2002, as described above. Those transactions that score above the cascade threshold 2003 are applied to the second neural network model 2005. The system outputs scores and reason codes from either the first model 2004 or the second model 2006, as appropriate.

The above-described cascading technique may be extended to include three or more neural network models, each having a corresponding cascade threshold.

Performance Monitor

The system periodically monitors its performance by measuring a performance metric comprising the fraud detection rate and the false positive rate. Other factors and statistics may also be incorporated into the performance metric. When the performance metric falls below a predetermined performance level, the system may either inform the user that the fraud model needs to be redeveloped, or it may proceed with model redevelopment automatically.

From the above description, it will be apparent that the invention disclosed herein provides a novel and advantageous method of detecting fraudulent use of customer accounts and account numbers, which achieves high detection rates while keeping false positive rates relatively low. The foregoing discussion discloses and describes merely exemplary methods and embodiments of the present invention. As will be understood by those familiar with the art, the invention may be embodied in many other specific forms. Other variables might be used in both the model development and transaction processing components.

Accordingly, the disclosure of the present invention is intended to be illustrative of the preferred embodiments and is not meant to limit the scope of the invention. The scope of the invention is to be limited only by the following claims.

Claims

1. A computer-implemented process for identifying and determining fraudulent transaction data in a computer-controlled transaction processing system (100) including predictive modeling means (108) for receiving current transaction data (805), processing the current transaction data, and outputting a plurality of output values (1005, 807), including a score value representing a likelihood of a fraudulent transaction, comprising the steps of:
prior to receiveng the current transaction data (805) for at least one current transaction:

- generating a consumer profile for each of a plurality of consumers from a plurality of past fraud-related variables (1123) and from consumer data (800), each consumer profile describing historical spending patterns of a corresponding consumer; the past fraud-related variables (1123) being derived by pre-processing past transaction data (804), the past transaction data including values for a plurality of transaction variables for a plurality of past transactions, the consumer data (806) including values for each consumer for a plurality of consumer variables;
- training the predictive modeling means (108) with the consumer profiles and with the past fraud-related variables to obtain a predictive model; and
- storing the obtained predictive model in the computer;

receiving current transaction data (805) for a current transaction of a consumer,
receiving consumer data (806) associated with the consumer;
receiving the consumer profile associated with the consumer;
pre-processing the obtained current transaction data (805), consumer data (806), and consumer profile to derive current fraud-related variables for the current transaction;
determining the likelihood of fraud in the current transaction by applying the current fraud-related variables to the predictive model; and
outputting from the predictive modeling means (108) an output signal (1005, 807) indicating the likelihood that the current transaction is fraudulent.

2. The process of claim 1, wherein the generating step comprises the substeps of:

receiving past transaction data (804) for a plurality of past transactions, the past transaction data providing values for a plurality of transaction variables;
receiving consumer data (806) for each of a plurality of consumers, the consumer data providing values for a plurality of consumer variables for each consumer;
pre-processing the past transaction data (804) to derive past fraud-related variables (1123) wherein at least some of the past fraud-related variables are not present in the plurality of variables in the past transaction data (804).

3. The process of claim 1 or 2, further comprising the step of updating the received consumer profile with the received current transaction data (805).

4. The process of one of the preceding claims, wherein the step of training the predictive modeling means comprises the substeps of:

applying the consumer profile and the derived past fraud-related variables to the predictive modeling means (108); ranking output data from the predictive modeling means as a function of a quality measurement;
adjusting the predictive modeling means as a function of the ranking step; and
repeating the applying, ranking, and adjusting steps until the quality measurement exceeds a predetermined level indicating that the predictive modeling means is adequately trained.

5. The process of one of the proceding claims, wherein the step of training the predictive modeling means comprises training a neural network (108) organized as a plurality of input processing elements (1001) for receiving the plurality of data values in the transaction data, a plurality of hidden processing elements (1003) coupled to the input processing elements (1001) for processing the transaction data, and a plurality of output processing elements (1004) coupled to the hidden processing elements (1003) for outputting the plurality of output values (1005, 807).

6. The process of claim 5, wherein the neural network (108) comprises a plurality of processing elements linked by connections characterized by weights, and the step of adjusting the neural network comprises the steps of:

selecting a subset of the weights to be decayed; and
decaying the selected subset of weights.

7. The process of one of the preceding claims, wherein the current transaction data (805), the consumer profile, and the consumer data (806) each comprise a plurality of data elements, further comprising, for at least one of the data elements the steps of:

determining a relative contribution value of the data element to the output signal indicating the likelihood that the current transaction is fraudulent;
determining a reason code which indicates a reason for the output signal as a function of the relative contribution value;
retrieving an explanation associated with the determined reason code value; and
outputting a computer signal indicative of the reason code and the explanation.

8. The process of one of the preceding claims further comprising the steps of:

monitoring a performance metric of the predictive modeling means (108), the performance metric comprising at least one of a fraud detection rate measurement and a false positive rate measurement;
comparing the performance metric with a predetermined performance level for the performance metric; and
in response to the predetermined performance level exceeding the performance metric, repeating the step of training the predictive modeling means (108).

9. The process of one of the preceding claims, wherein the past fraud-related variables (1123) and the current fraud-related variables each comprise at least:

transaction dollar amounts of past transactions;
transaction dates and times of past transactions;
transaction approvals and declines of past transactions; risk groups of past transactions; and
merchants of past transactions.

10. The process of claim 1, wherein the step of training the predictive modeling means comprises training a neural network (108) in the computer-controlled transaction processing system (100), said system (100) comprising:

a computer-readable memory (102); and
the neural network (108) comprising a plurality of interconnected processing elements (1002, 1003, 1004), each processing element being in a layer of the neural network, each layer having a distance to an input layer, each processing element comprising:

- a plurality of inputs (x);
- a plurality of weights (w), each weight (w) associated with a corresponding input (x) to form weighted inputs;
- a summation function (902) for combining the weighted inputs; and
- a transfer function (903) for processing the combined weighted inputs into an output (z);

characterized by the steps of:
iteratively decaying the weights of at least one processing element by a cost function that varies a decay rate for decaying the weights by a function of the distance of the input layer from the layer containing the processing element.

11. The process of claim 10, wherein the cost function is of the form:

$$\frac{1}{2}\sum_{k \in D}(target_k - output_k)^2 + g\lambda\sum_{i \in W}(c_i\omega_i^2 - \frac{1}{1+|\omega_i|})$$

wherein:

- D represents a data set;
- $target_k$ represents a target value for an element k of the data set;
- $output_k$ represents a neural network output for element k of the data set;
- g represents an interlayer gain multiplier that varies as a function of the distance between the input layer and the layer containing the processing element;
- λ represents the relative importance of the decay rate term;
- W represents a weight set;

- ω_i represents a value of weight i; and
- c_i represents a constant.

12. A computer-controlled transaction processing system (100) including predictive modeling means (108) for receiving current transaction data (805), processing the current transaction data, and outputting a plurality of output values (1005, 807), including a score value representing a likelihood of a fraudulent transaction, including a model development component for developing a predictive model, comprising:

    - means for receiving past transaction data (804) for a plurality of past transactions, the past transaction data providing values for a plurality of transaction variables;
    - means for receiving consumer data (806) for each of a plurality of consumers, the consumer data providing values for a plurality of consumer variables for each consumer;
    - means for pre-processing the past transaction data (804) to derive past fraud-related variables (1123) wherein at least some of the past fraud-related variables are not present in the plurality of variables in the past transaction data (804);
    - means for generating a consumer profile for each individual consumer, from the past fraud-related variables (1123) and the received consumer data (806), the consumer profile describing historical spending patterns of the consumer;
    - means for training the predictive model with the consumer profiles and with the past fraud-related variables; and
    - means for storing the trained predictive model in the computer; and

    a model application component, for applying the trained predictive model, comprising:

    - means for receiving current transaction data (805) for a transaction of a consumer;
    - means for receiving consumer data (806) associated with the consumer;
    - means for receiving the consumer profile asociated with the consumer;
    - a current transaction data pre-processor, for pre-processing the obtained current transaction data (805), consumer data (806), and consumer profile to derive current fraud-related variables for the current transaction;
    - means for determining the likelihood ot fraud in the current transaction by applying the current fraud-related variables to the predictive model; and
    - means for outputting from the predictive model an output signal (1005, 807) indicating the likelihood that the current transaction is fraudulent.

Patentansprüche

1. Auf einem Rechner realisiertes Verfahren zum Identifizieren und Ermitteln betrügerischer Transaktionsdaten in einem rechnergesteuerten Transaktionsverarbeitungssystem (100) mit einer Prädiktionsmodellvorrichtung (108) zum Empfangen aktueller Transaktionsdaten (805), Verarbeiten der aktuellen Transaktionsdaten und Ausgeben mehrere Ausgangswerte (1005, 807), einschließlich einem Trefferwert, der eine Wahrscheinlichkeit einer betrügerischen Transaktion wiedergibt, mit folgenden Verfahrensschritten: vor dem Empfangen der aktuellen Transaktionsdaten (805) für wenigstens eine aktuelle Transaktion:

    - Erzeugen eines Verbraucherprofils für jeden von mehreren Verbrauchern aus einer Vielzahl vergangener betrugsbezogener Variablen (1123) und aus Verbraucherdaten (806), wobei jedes Verbraucherprofil frühere Ausgabemuster eines entsprechenden Verbrauchers beschreibt; wobei die vergangenen betrugsbezogenen Variablen (1123) durch Vorverarbeiten vergangener Transaktionsdaten (804) abgeleitet werden, die vergangenen Transaktionsdaten für mehrere Transaktionsvariablen Werte für eine Vielzahl vergangener Transaktionen enthalten, und die Verbraucherdaten (806) für jeden Verbraucher Werte für eine Vielzahl Verbrauchervariablen umfassen;
    - Trainieren der Prädiktionsmodellvorrichtung (108) mit den Verbraucherprofilen und mit den vergangenen betrugsbezogenen Variablen, um ein prädiktives Modell zu erhalten; und
    - Speichern des erhaltenen prädiktiven Modells in dem Rechner;

    Empfangen der aktuellen Transaktionsdaten (805) für eine aktuelle Transaktion eines Verbrauchers;
    Empfangen von Verbraucherdaten (806), welche zu dem Verbraucher gehören;
    Empfangen des Verbraucherprofils, welches zu dem Verbraucher gehört;
    Vorverarbeiten der erhaltenen aktuellen Transaktionsdaten (805), Verbraucherdaten (806) und des Verbrau-

cherprofils, um aktuelle betrugsbezogene Variablen für die aktuelle Transaktion abzuleiten;
Ermitteln der Wahrscheinlichkeit eines Betrugs bei der aktuellen Transaktion durch Anwenden der aktuellen betrugsbezogenen Variablen auf das prädiktive Modell; und
Ausgeben eines Ausgangssignals (1005, 807) aus der Prädiktionsmodellvorrichtung (108), welches die Wahrscheinlichkeit angibt, daß die aktuelle Transaktion betrügerisch ist.

2. Verfahren nach Anspruch 1, bei dem der Schritt des Erzeuqens die folqenden Unterschritte umfaßt:

- Empfangen vergangener Transaktionsdaten (804) aus mehreren vergangenen Transaktionen, wobei die vergangen Transaktionsdaten Werte für mehrere Transaktionsvariablen vorsehen;
- Empfangen von Verbraucherdaten (806) für jeden von mehreren Verbrauchern, wobei die Verbraucherdaten Werte für eine Vielzahl Verbrauchervariablen für jeden Verbraucher vorsehen;
- Vorverarbeiten der vergangenen Transaktionsdaten (804), um vergangene betrugsbezogenen Variablen (1123) abzuleiten, wobei wenigstens einige der vergangenen betrugsbezogenen Variablen in der Vielzahl der Variablen der vergangenen Transaktionsdaten (804) nicht vorkommen.

3. Verfahren nach Anspruch 1 oder 2, bei dem ferner das empfangene Verbraucherprofil mit den empfangenen aktuellen Transaktionsdaten (805) aktualisiert wird.

4. Verfahren nach einem der vorangehenden Ansprüche, bei dem der Schritt des Trainierens der Prädiktionsmodellvorrichtung folgenden Unterschritte umfaßt:

- Anlegen des Verbraucherprofils und der abgeleiteten vergangenen betrugsbezogenen Variablen an die Prädiktionsmodellvorrichtung (108);
- Ordnen der Ausgangsdaten von der Prädiktionsmodellvorrichtung nach einer Rangordnung als eine Funktion einer Qualitätsmessung;
- Einstellen der Prädiktionsmodellvorrichtung als eine Funktion des Rangordnungsschrittes;
- Wiederholen der Schritte Anlegen, Ordnen nach Rangordnung und Einstellen, bis die Qualitätsmessung einen vorgegebenen Schwellwert überschreitet, welcher anzeigt, daß die Prädiktionsmodellvorrichtung angemessen trainiert ist.

5. Verfahren nach einem der vorangehenden Ansprüche, bei dem der Schritt des Trainierens der Prädiktionsmodellvorrichtung das Trainieren eines neuralen Netzes (108) umfaßt, welches in mehreren Eingangsverarbeitungselementen (1001) organisiert ist, um die mehreren Datenwerte in den Transaktionsdaten zu empfangen, wobei mehrere versteckte Verarbeitungselemente (1003) mit den Eingangsverarbeitungselementen (1001) verbunden sind, um die Transaktionsdaten zu verarbeiten, und mehrere Ausgangsverarbeitungselemente (1004) mit den verborgenen Eingangselementen (1003) verbunden sind, um die mehreren Ausgangswerte (1005, 807) auszugeben.

6. Verfahren nach Anspruch 5, bei dem das neurale Netz (1008) mehrere Verarbeitungselemente aufweist, welche über Verbindungen miteinander verknüpft sind, die durch Gewichte gekennzeichnete sind, und bei dem das Einstellen des neuralen Netzes die folgenden Unterschritte umfaßt:

- Auswählen einer Untergruppe der Gewichte, welche abklingen sollen; und
- Abklingenlassen der ausgewählten Untergruppe der Gewichte.

7. Verfahren nach einem der vorangehenden Ansprüche, bei dem die aktuellen Transaktionsdaten (805), das Verbraucherprofil und die Verbraucherdaten (806) jeweils mehrere Datenelemente aufweisen, und mit den folgenden weiteren Schritten für wenigstens eines der Datenelemente:

- Ermitteln eines relativen Beitragswertes des Daten-elementes zu dem Ausgangssignal, welches die Wahrscheinlichkeit angibt, daß die aktuelle Transaktion betrügerisch ist;
- Ermitteln eines Grund-Codes, welcher einen Grund für das Ausgangssignal als eine Funktion des relativen Beitragswertes angibt;
- Rückgewinnen einer Erklärung, welche zu dem ermittelten Grund-Codewert gehört;
- Ausgeben eines Rechnersignals, welches den Grund-Code und die Erklärung angibt.

8. Verfahren nach einem der vorangehenden Ansprüche, mit den weiteren Verfahrensschritten:

Überwachen eines Leistungsmaßes der Prädiktionsmodellvorrichtung (108), wobei das Leistungsmaß wenigstens eine Betrugserfassungsraten-Messung und eine falsche positive Ratenmessung umfaßt;
Vergleichen des Leistungsmaßes mit einem vorgegebenen Leistungspegel für das Leistungsmaß; und
abhängig davon, daß der vorgegebene Leistungspegel das Leistungsmaß überschreitet, Wiederholen des Trainierens der Prädiktionsmodellvorrichtung (108).

9. Verfahren nach einem der vorangehenden Ansprüche, bei dem die vergangenen betrugsbezogenen Variablen (1123) und die aktuellen betrugsbezogenen Variablen jeweils wenigstens folgende Komponenten umfassen:

Transaktions-Dollarmengen vergangener Transaktionen; Transaktionsdaten und Zeiten der vergangenen Transaktionen;
Transaktionsbestätigungen und -verweigerungen vergangener Transaktionen;
Risikogruppen vergangener Transaktionen; und
Händler vergangener Transaktionen.

10. Verfahren nach Anspruch 1, bei dem das Trainieren der Prädiktionsmodellvorrichtung das Trainieren eines neuralen Netzes (108) in dem rechnergesteuerten Transaktionsverarbeitungssystem (100) umfaßt, wobei das System (100) einen Rechner-lesbaren Speicher (102) aufweist, und wobei das neurale Netz (108) mehrere miteinander verbundene Verarbeitungselemente (1002, 1003, 1004) aufweist, jedes Verarbeitungselement in einer Ebene des neuralen Netzes liegt, jede Ebene einen Abstand zu einer Eingangsebene hat, und jedes Verarbeitungselement folgende Merkmale aufweist:

mehrere Eingänge (x);
mehrere Gewichte (w), wobei jedes Gewicht (w) einem entsprechenden Eingang (x) zugeordnet ist, um gewichtete Eingänge zu bilden;
eine Summenfunktion (902) zum Kombinieren der gewichteten Eingänge; und
eine Übertragungsfunktion (903) zum Verarbeiten der kombinierten gewichteten Eingänge zu einem Ausgang (z); dadurch **gekennzeichnet**, daß die Gewichte wenigstens eines Verarbeitungselementes iterativ mit einer Kostenfunktion abklingen, welche eine Abklingrate zum Verringern der Gewichte als eine Funktion des Abstandes der Eingangsebene von der das Verarbeitungselement enthaltenden Ebene variiert.

11. Verfahren nach Anspruch 10, bei dem die Kostenfunktion folgende Form hat:

$$\tfrac{1}{2} \sum_{k \in D} (\text{target}_k - \text{output}_k)^2 + g\lambda \sum_{i \in \omega} \left(c_1\, \omega_i^2 - \frac{1}{1 + |\omega_i|}\right),$$

wobei

- D einen Datensatz wiedergibt;
- target_k gibt einen Sollwert für ein Element k des Datensatzes wieder;
- output_k gibt einen Ausgang des neuralen Netzes für das Element k des Datensatzes wieder;
- g gibt einen zwischenebenen Verstärkungs-Multiplikator wieder, welcher sich als eine Funktion des Abstands zwischen der Eingangsebene und der das Verarbeitungselement enthaltenden Ebene ändert;
- λ gibt die relative Wichtigkeit des Abklingratenterms wieder;
- W gibt einen Satz Gewichte wieder;
- ω_i gibt einen Wert des Gewichtes i wieder; und
- c_1 gibt eine Konstante wieder.

12. Rechnergesteuertes Transaktionsverarbeitungssystem (100) mit einer Prädiktionsmodellvorrichtung (108) zum Empfangen aktueller Transaktionsdaten (805), Verarbeiten der Transaktionsdaten und Ausgeben mehrerer Ausgangswerte (105, 807), einschließlich eines Trefferwertes, welcher eine Wahrscheinlichkeit einer betrügerischen Transaktion wiedergibt; mit einer Modellentwicklungskomponente zum Entwickeln eines prädiktiven Modells, welche folgende Merkmale aufweist:

- eine Vorrichtung zum Empfangen vergangener Transaktionsdaten (804) für mehrere vergangene Transaktio-

nen, wobei die vergangenen Transaktionsdaten Werte für mehrere Transaktionsvariablen vorsehen;

- eine Vorrichtung zum Empfangen von Verbraucherdaten (806) für jeden von mehreren Verbrauchern, wobei die Verbraucherdaten Werte für mehrere Verbrauchervariablen für jeden Verbraucher vorsehen;
- eine Vorrichtung zum Vorverarbeiten der vergangenen Transaktionsdaten (804), um vergangene betrugsbezogene Variablen (1123) abzuleiten, wobei wenigstens einige der vergangenen betrugsbezogenen Variablen in den mehreren Variablen der vergangenen Transaktionsdaten (804) nicht vorkommt;
- eine Vorrichtung zum Erzeugen eines Verbraucherprofils für jeden einzelnen Verbraucher aus den vergangenen betrugsbezogenen Variablen (1123) und den empfangenen Verbraucherdaten (806), wobei das Verbraucherprofil vorhergehende Ausgabemuster des Verbrauchers beschreibt;
- eine Vorrichtung zum Trainieren des pädiktiven Modells mit den Verbraucherprofilen und mit den vergangenen betrugsbezogenen Variablen; und
- eine Vorrichtung zum Speichern des trainierten prädiktiven Modells in dem Rechner; und

mit einer Modellanwendungskomponente zum Anwenden des trainierten prädiktiven Modells, welche folgende Merkmale aufweist:

- eine Vorrichtung zum Empfangen aktueller Transaktionsdaten (805) für eine Transaktion eines Verbrauchers;
- eine Vorrichtung zum Empfangen von Verbraucherdaten (806), welche zu dem Verbraucher gehören;
- eine Vorrichtung zum Empfangen des Verbraucherprofils, welches zu dem Verbraucher gehört;
- eine Vorrichtung zum Vorverarbeiten aktueller Transaktionsdaten für die Vorverarbeitung der erhaltenen aktuellen Transaktionsdaten (805) der Benutzerdaten (806) und des Verbraucherprofils, um aktuelle betrugsbezogene Variablen für die aktuelle Transaktion abzuleiten;
- eine Vorrichtung zum Ermitteln der Wahrscheinlichkeit eines Betrugs bei der aktuellen Transaktion durch Anwenden der aktuellen betrugsbezogenen Variablen auf das prädiktive Modell;
- eine Vorrichtung zum Ausgeben eines Ausgangssignals (1005, 807) aus dem prädiktiven Modell, welches die Wahrscheinlichkeit, daß die aktuelle Transaktion betrügerisch ist, angibt.

Revendications

1. Procédé informatique pour identifier et déterminer des données de transactions frauduleuses dans un système de transaction informatique (100) comprenant un moyen de modélisation prédictive (108) pour recevoir des données de transaction en cours (805), traiter les données de transactions en cours et fournir plusieurs valeurs de sortie (1005, 807) incluant une valeur de score représentant une probabilité de transaction frauduleuse, comprenant les étapes suivantes :

   avant de recevoir les données de transaction en cours (805) pour au moins une transaction en cours :

   - produire un profil de consommateur pour chacun de plusieurs consommateurs à partir de plusieurs variables passées associées à une fraude (1123) et à partir de données de consommateur (806), chaque profil de consommateur décrivant un historique des configurations de dépense du consommateur correspondant ; les variables antérieures associées à une fraude (1123) étant associées à des données de transaction passées de pré-traitement (804), les données de transaction passées comprenant des valeurs pour plusieurs variables de transaction pour plusieurs transactions antérieures, les données de consommateur (806) comprenant des valeurs pour chaque consommateur pour plusieurs variables de consommateur ;
   - réaliser l'apprentissage du moyen de modélisation prédictive (108) avec les profils de consommateur et avec les variables passées associées à une fraude pour obtenir un modèle prédictif ; et
   - mémoriser le modèle prédictif obtenu dans l'ordinateur ;

   recevoir des données de transaction (805) pour une transaction en cours d'un consommateur ;
   recevoir des données de consommateur (806) associées au consommateur ;
   recevoir le profil de consommateur associé au consommateur ;
   pré-traiter les données de transaction en cours obtenues (805), les données de consommateur (806) et le profil de consommateur pour en déduire des variables en cours associées à une fraude pour la transaction en cours ;
   déterminer la probabilité de fraude dans la transaction en cours en appliquant les variables en cours associées à une fraude au modèle prédictif ; et
   fournir à partir du moyen de modélisation prédictive (108) un signal de sortie (1005, 807) indiquant la probabilité pour que la transaction en cours soit frauduleuse.

2. Procédé selon la revendication 1, dans lequel l'étape consistant à produire un profil comprend les sous-étapes suivantes :

recevoir des données de transaction passées (804) pour plusieurs transactions passées, les données de transaction passées fournissant des valeurs pour plusieurs variables de transaction ;
recevoir des données de consommateur (806) pour chacun de plusieurs consommateurs, les données de consommateur fournissant des valeurs pour plusieurs variables de consommateur pour chaque consommateur ;
pré-traiter les données de transaction passées (804) pour fournir des variables passées associées à une fraude (1123) dans lesquelles au moins certaines des variables passées associées à une fraude ne sont pas présentes dans la pluralité de variables des données de transaction passées (804).

3. Procédé selon la revendication 1 ou 2, comprenant l'étape consistant à mettre à jour le profil de consommateur reçu avec les données de transaction courantes reçues (805).

4. Procédé selon l'une des revendications précédentes dans lequel l'étape d'apprentissage du moyen de modélisation prédictive comprend les étapes suivantes :

appliquer le profil de consommateur et les variables passées obtenues associées à une fraude au moyen de modélisation prédictive (108) ;
ranger les données de sortie en provenance du moyen de modélisation prédictive en fonction d'une mesure de qualité ;
régler le moyen de modélisation prédictive en fonction de l'étape de rangement ; et
répéter les étapes d'application de rangement et de réglage jusqu'à ce que la mesure de qualité dépasse un niveau prédéterminé indiquant que le moyen de modélisation prédictive a subi un apprentissage adéquat.

5. Procédé selon l'une des revendications précédentes dans lequel l'étape d'apprentissage du moyen de modélisation prédictive comprend l'apprentissage d'un réseau neuronal (108) organisé sous forme d'une pluralité d'éléments de traitement d'entrée (1001) pour recevoir la pluralité de valeurs de données dans les données de transaction, d'une pluralité d'éléments de traitement cachés (1003) couplés aux éléments de traitement d'entrée (1001) pour traiter les données de transaction, et d'une pluralité d'éléments de traitement de sortie (1004) couplés aux éléments de traitement cachés (1003) pour fournir la pluralité de valeurs de sortie (1005, 807).

6. Procédé selon la revendication 5, dans lequel le réseau neuronal (108) comprend plusieurs éléments de traitement liés par des connexions caractérisées par des poids, et l'étape de réglage du réseau neuronal comprend les étapes suivantes :

sélectionner un sous-ensemble de poids à faire décroître ; et
faire décroître le sous-ensemble choisi de poids.

7. Procédé selon l'une des revendications précédentes dans lequel les données de transaction courantes (805), le profil de consommateur et les données de consommateur (806) comprennent chacune plusieurs éléments de données, comprenant en outre, pour au moins un des éléments de données, les étapes suivantes :

déterminer une valeur de contribution relative de l'élément de données sur le signal de sortie indiquant la probabilité pour que la transaction en cours soit frauduleuse ;
déterminer un code de raison qui indique une raison pour le signal de sortie en fonction de la valeur de contribution relative ;
retrouver une explication associée à la valeur de code de raison déterminée ; et
fournir un signal d'ordinateur indicatif du code de raison et de l'explication.

8. Procédé selon l'une des revendications précédentes, comprenant en outre les étapes suivantes :

surveiller une métrique de performance du moyen de modélisation prédictive (108), la métrique de performance comprenant au moins une mesure de taux de détection de fraude et une mesure de taux positif faux ;
comparer la métrique de performance à un niveau de performance prédéterminée de la métrique de performance ; et
en réponse au fait que le niveau de performance prédéterminé dépasse la métrique de performance, répéter

l'étape d'apprentissage du moyen de modélisation prédictive (108).

9. Procédé selon l'une des revendications précédentes dans lequel les variables passées associées à une fraude (1123) et les variables en cours associées à une fraude comprennent au moins :

les montants en dollars de transactions passées ;
les dates et les heures de transactions passées ;
les approbations et les refus de transactions passées ;
des groupes de risques de transactions passées ; et
les vendeurs de transactions passées.

10. Procédé selon la revendication 1, dans lequel l'étape d'apprentissage du moyen de modélisation prédictive comprend l'apprentissage d'un réseau neuronal (108) dans le système informatique de traitement de transactions (100), le système (100) comprenant :

une mémoire lisible par un ordinateur (102) ; et
le réseau neuronal (108) comprenant une pluralité d'éléments de traitement interconnectés (1002, 1003, 1004), chaque élément de traitement étant dans une couche du réseau neuronal, chaque couche ayant une distance à une couche d'entrée, chaque élément de traitement comprenant :

- une pluralité d'entrées (x) ;
- une pluralité de poids (w), chaque poids (w) étant associé à une entrée correspondante (x) pour former des entrées pondérées ;
- une fonction de sommation (902) pour combiner les entrées pondérées ; et
- une fonction de transfert (903) pour traiter les entrées pondérées combinées en une sortie (z) ;

caractérisé par l'étape consistant à faire décroître itérativement les poids d'au moins un élément de traitement par une fonction de coût qui fait varier une cadence de décroissance pour faire décroître les poids en fonction de la distance à la couche d'entrée de la couche contenant l'élément de traitement.

11. Procédé selon la revendication 10, dans lequel la fonction de coût est du type suivant :

$$\frac{1}{2}\sum_{k \in D}\left(\mathrm{target}_k - \mathrm{output}_k\right)^2 + g\lambda \sum_{i \in W}\left(c_i\,\omega_i^2 - \frac{1}{1+|\omega_i|}\right)$$

dans laquelle :

- D représente un ensemble de données ;
- target_k représente une valeur de cible pour un élément k de l'ensemble de données ;
- output_k représente une sortie de réseau neuronal pour l'élément k de l'ensemble de données ;
- g représente un multiplieur de gain intercouche qui varie en fonction de la distance entre la couche d'entrée et la couche contenant l'élément de traitement ;
- λ représente l'importance relative du terme de cadence de décroissance ;
- W représente un ensemble de poids ;
- ω_i représente une valeur de poids i ; et
- c_i représente une constante.

12. Système informatique de traitement de transactions (100) comprenant un moyen de modélisation prédictive (108) pour recevoir des données de transaction courantes (805), pour traiter les données de transaction courantes, et fournir une pluralité de valeurs de sortie (1005, 807), incluant une valeur de score représentant une probabilité de transaction frauduleuse, comprenant une composante de développement de modèle pour développer un modèle prédictif, comprenant :

- un moyen pour recevoir des données de transaction passées (804) pour plusieurs transactions passées, les données de transaction passées fournissant des valeurs pour plusieurs variables de transaction ;
- un moyen pour recevoir des données de consommateur (806) pour chacun de plusieurs consommateurs, les

données de consommateur fournissant des valeurs pour plusieurs variables de consommateur pour chaque consommateur ;

- un moyen pour pré-traiter les données de transaction passées (804) pour fournir des variables passées associées à une fraude (1123) dans lesquelles au moins certaines des variables passées associées à une fraude ne sont pas présentes dans la pluralité de variable des données de transaction passées (804) ;
- des moyens pour produire un profil de consommateur pour chaque consommateur individuel à partir des variables passées associées à une fraude (1123) et des données de consommateur reçues (806), le profil de consommateur décrivant un historique des configurations de dépenses du consommateur ;
- des moyens pour réaliser l'apprentissage du modèle prédictif avec les profils de consommateur et avec les variables passées liées à une fraude ; et
- des moyens pour mémoriser le modèle prédictif ayant subi l'apprentissage dans l'ordinateur ; et
- une composante d'application de modèle pour appliquer le modèle prédictif ayant subi l'apprentissage, comprenant :
- des moyens pour recevoir des données de transaction en cours (805) pour une transaction d'un consommateur ;
- des moyens pour recevoir des données de consommateur (806) associées au consommateur ;
- des moyens pour recevoir le profil de consommateur associé au consommateur ;
- un pré-processeur de données de transaction en cours pour pré-traiter les données de transaction en cours obtenues (805), les données de consommateur (806) et le profil de consommateur pour fournir des variables courantes associées à une fraude pour la transaction en cours ;
- des moyens pour déterminer la probabilité de fraude dans la transaction en cours en appliquant les variables courantes associées à une fraude au modèle prédictif ; et
- des moyens pour fournir à partir du modèle prédictif un signal de sortie (1005, 807) indiquant la probabilité pour que la transaction en cours soit frauduleuse.

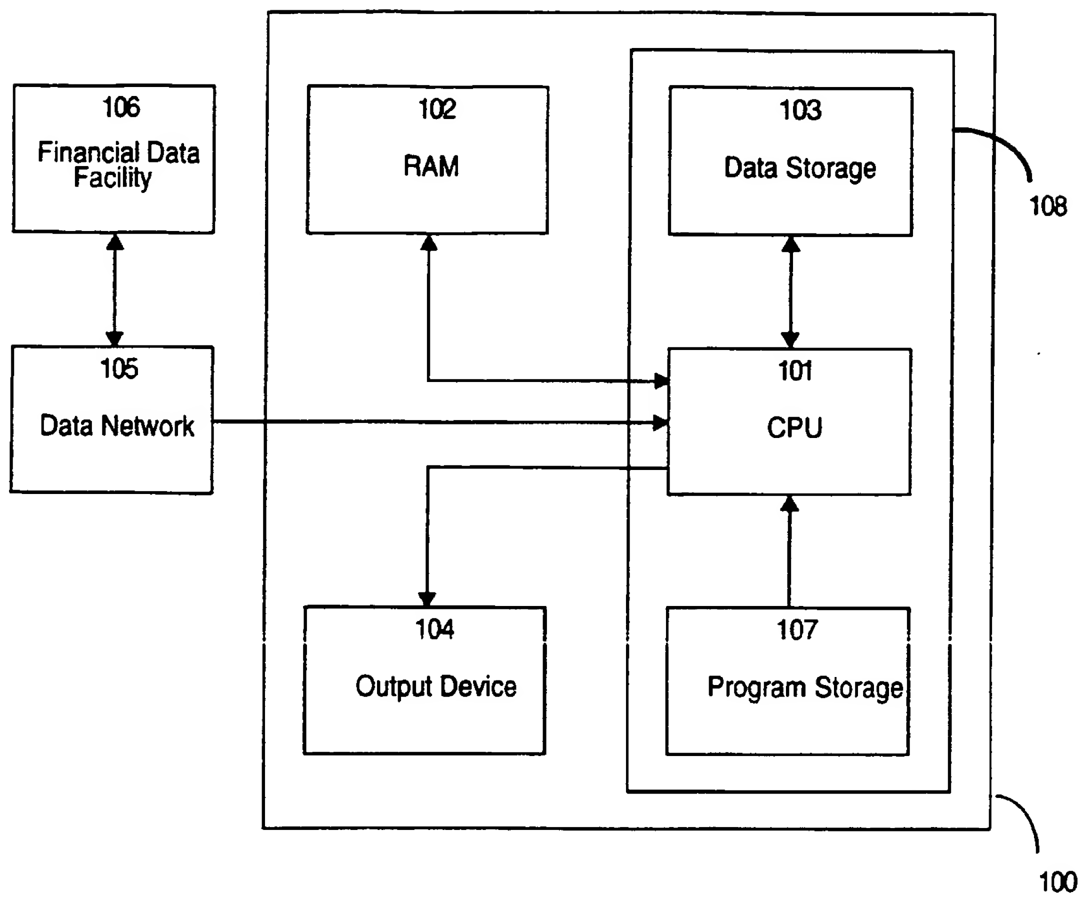

106
Financial Data
Facility
102
RAM
103
Data Storage
108
105
Data Network
101
CPU
104
Output Device
107
Program Storage
100

FIGURE 1

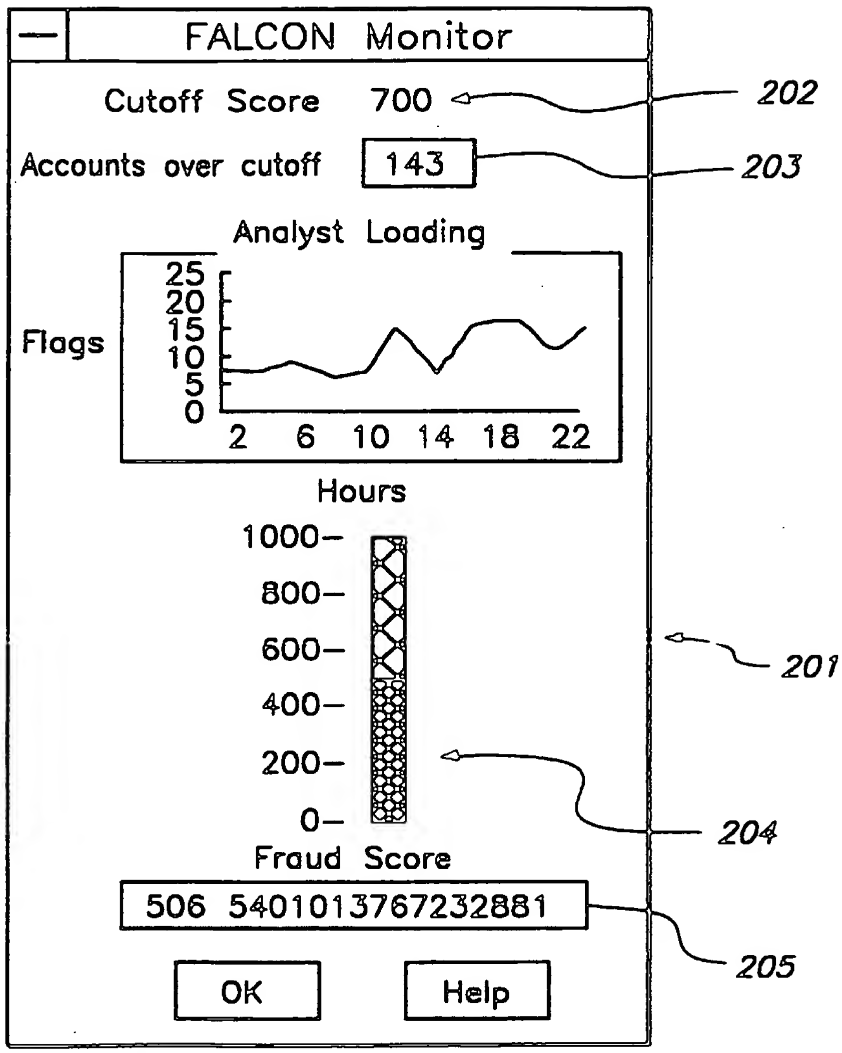

FALCON Monitor
Cutoff Score 700
Accounts over cutoff
143
Analyst Loading
Flags
25
20
15
10
5
0
2 6 10 14 18 22
Hours
1000
800
600
400
200
0
Fraud Score
506 5401013767232881
OK
Help
201
202
203
204
205

FIGURE 2

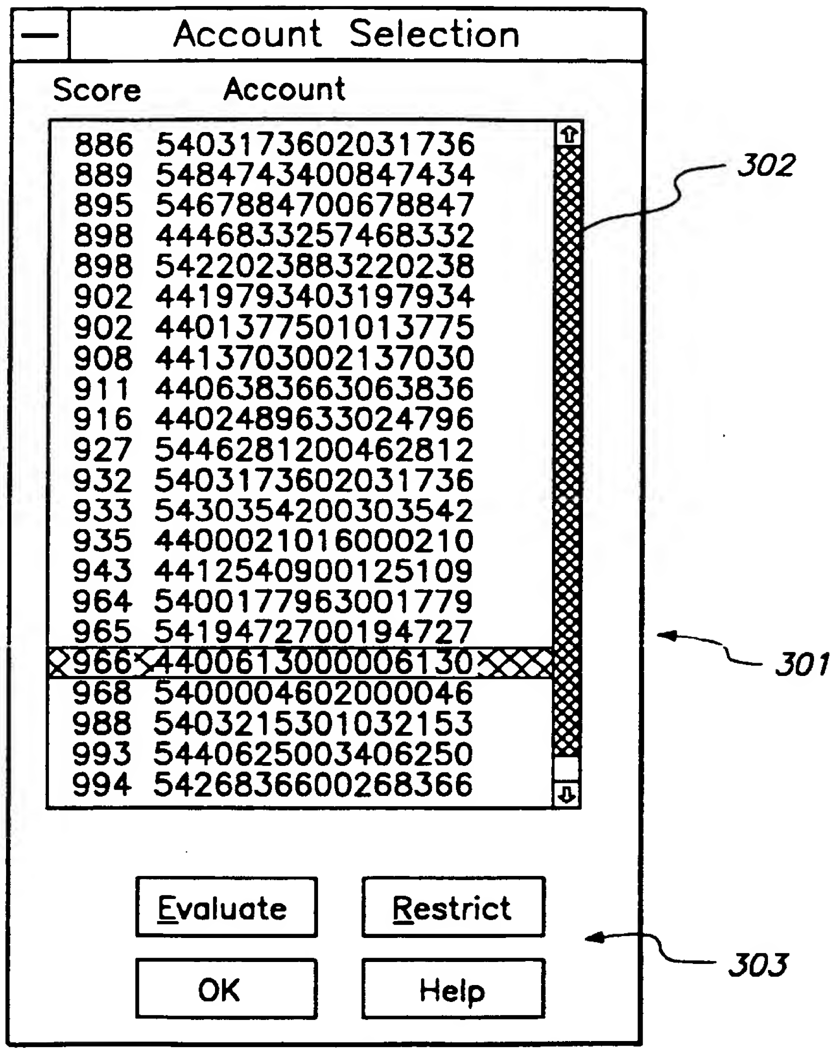

Account Selection
Score
Account
886 5403173602031736
889 5484743400847434
895 5467884700678847
898 4446833257468332
898 5422023883220238
902 4419793403197934
902 4401377501013775
908 4413703002137030
911 4406383663063836
916 4402489633024796
927 5446281200462812
932 5403173602031736
933 5430354200303542
935 4400021016000210
943 4412540900125109
964 5400177963001779
965 5419472700194727
966 4400613000006130
968 5400004602000046
988 5403215301032153
993 5440625003406250
994 5426836600268366
Evaluate
Restrict
OK
Help
302
301
303

FIGURE 3

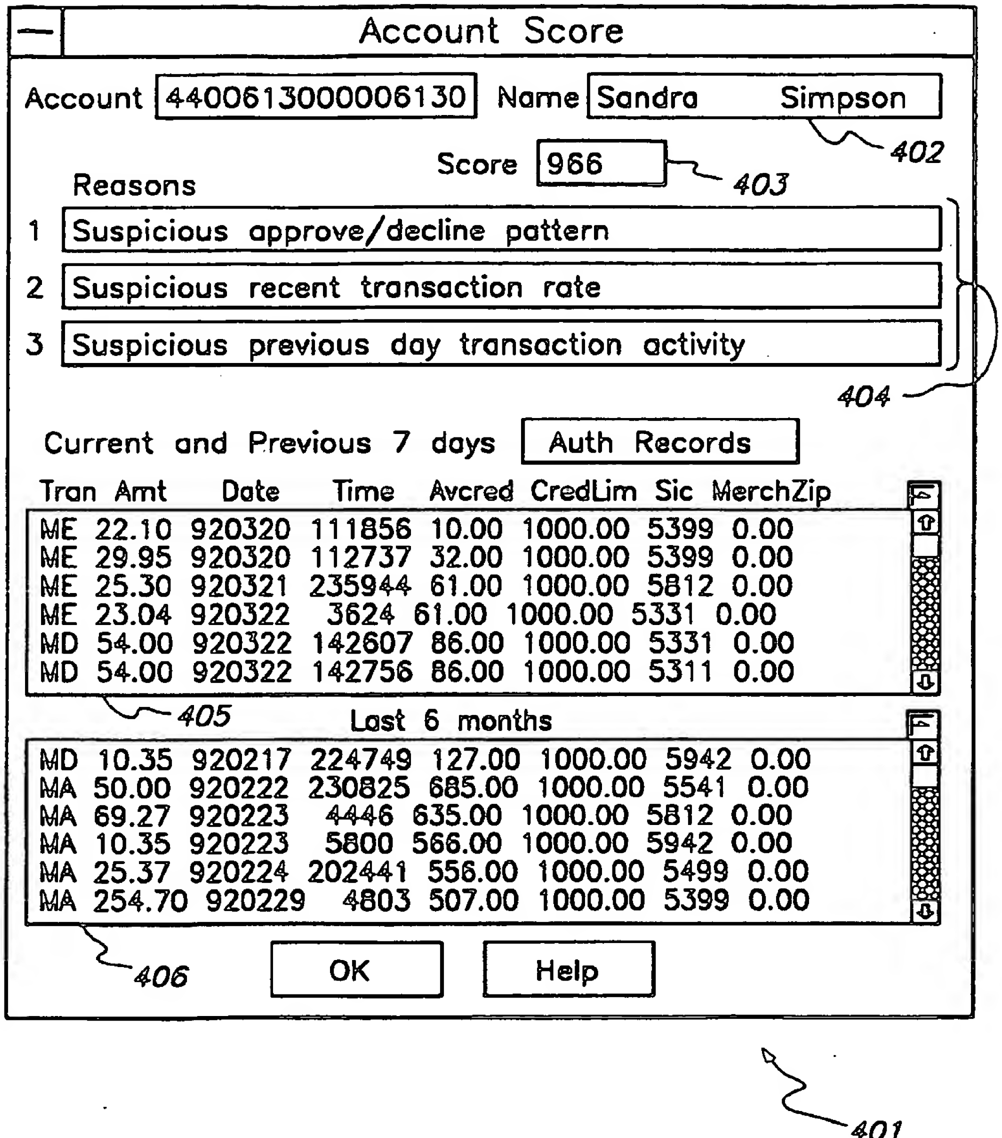

Account Score
Account 4400613000006130 Name Sandra Simpson
402
Score 966
403
Reasons
1 Suspicious approve/decline pattern
2 Suspicious recent transaction rate
3 Suspicious previous day transaction activity
404
Current and Previous 7 days
Auth Records
Tran Amt Date Time Avcred CredLim Sic MerchZip
ME 22.10 920320 111856 10.00 1000.00 5399 0.00
ME 29.95 920320 112737 32.00 1000.00 5399 0.00
ME 25.30 920321 235944 61.00 1000.00 5812 0.00
ME 23.04 920322 3624 61.00 1000.00 5331 0.00
MD 54.00 920322 142607 86.00 1000.00 5331 0.00
MD 54.00 920322 142756 86.00 1000.00 5311 0.00
405
Last 6 months
MD 10.35 920217 224749 127.00 1000.00 5942 0.00
MA 50.00 920222 230825 685.00 1000.00 5541 0.00
MA 69.27 920223 4446 635.00 1000.00 5812 0.00
MA 10.35 920223 5800 566.00 1000.00 5942 0.00
MA 25.37 920224 202441 556.00 1000.00 5499 0.00
MA 254.70 920229 4803 507.00 1000.00 5399 0.00
406
OK
Help
401

FIGURE 4

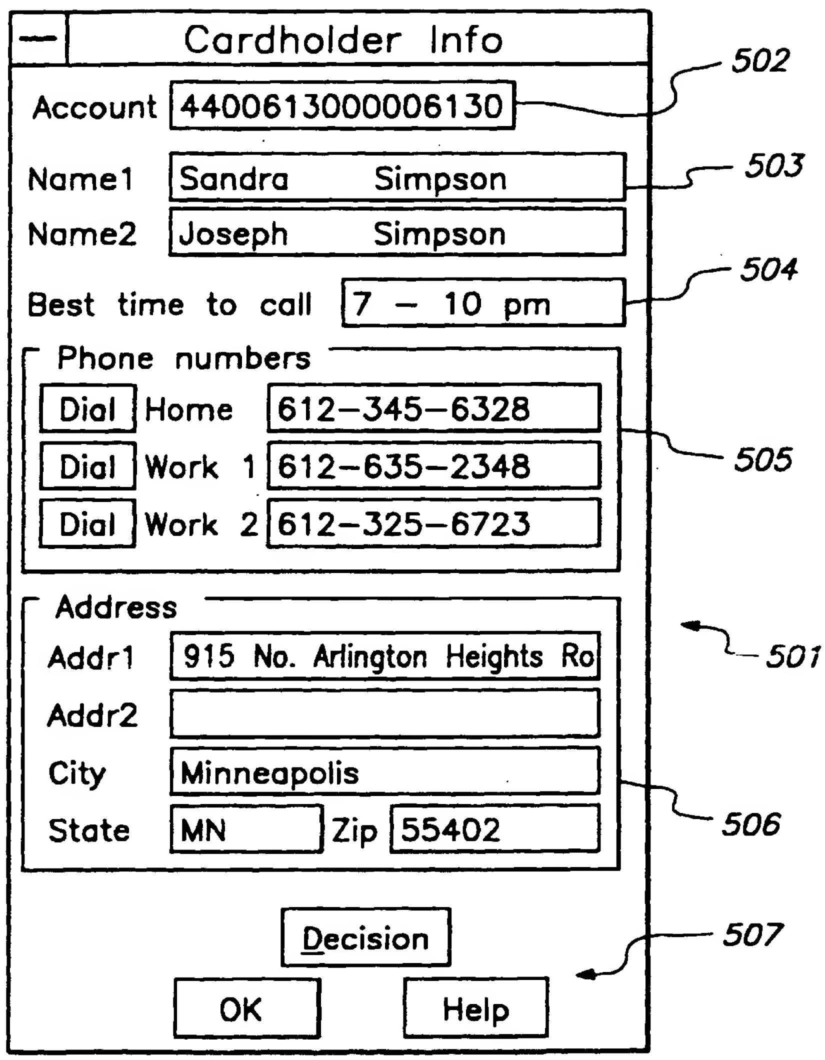

Cardholder Info
Account
4400613000006130
Name1
Sandra Simpson
Name2
Joseph Simpson
Best time to call
7 – 10 pm
Phone numbers
Dial
Home
612–345–6328
Dial
Work 1
612–635–2348
Dial
Work 2
612–325–6723
Address
Addr1
915 No. Arlington Heights Ro
Addr2
City
Minneapolis
State
MN
Zip
55402
Decision
OK
Help
502
503
504
505
501
506
507

FIGURE 5

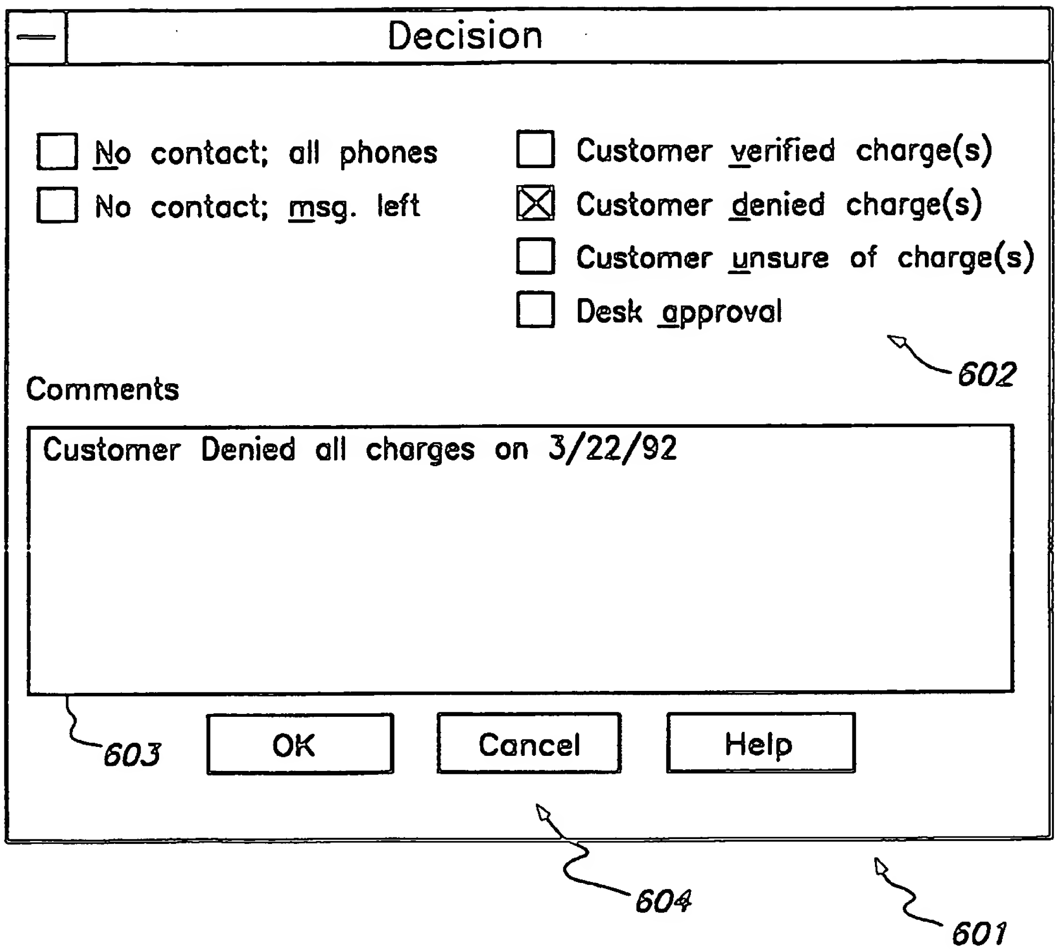

Decision
No contact; all phones
No contact; msg. left
Customer verified charge(s)
Customer denied charge(s)
Customer unsure of charge(s)
Desk approval
602
Comments
Customer Denied all charges on 3/22/92
603
OK
Cancel
Help
604
601

FIGURE 6

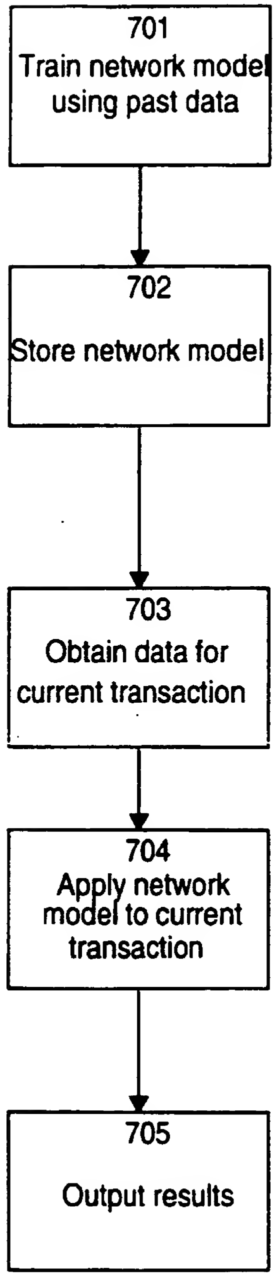

701
Train network model using past data
702
Store network model
703
Obtain data for current transaction
704
Apply network model to current transaction
705
Output results

FIGURE 7

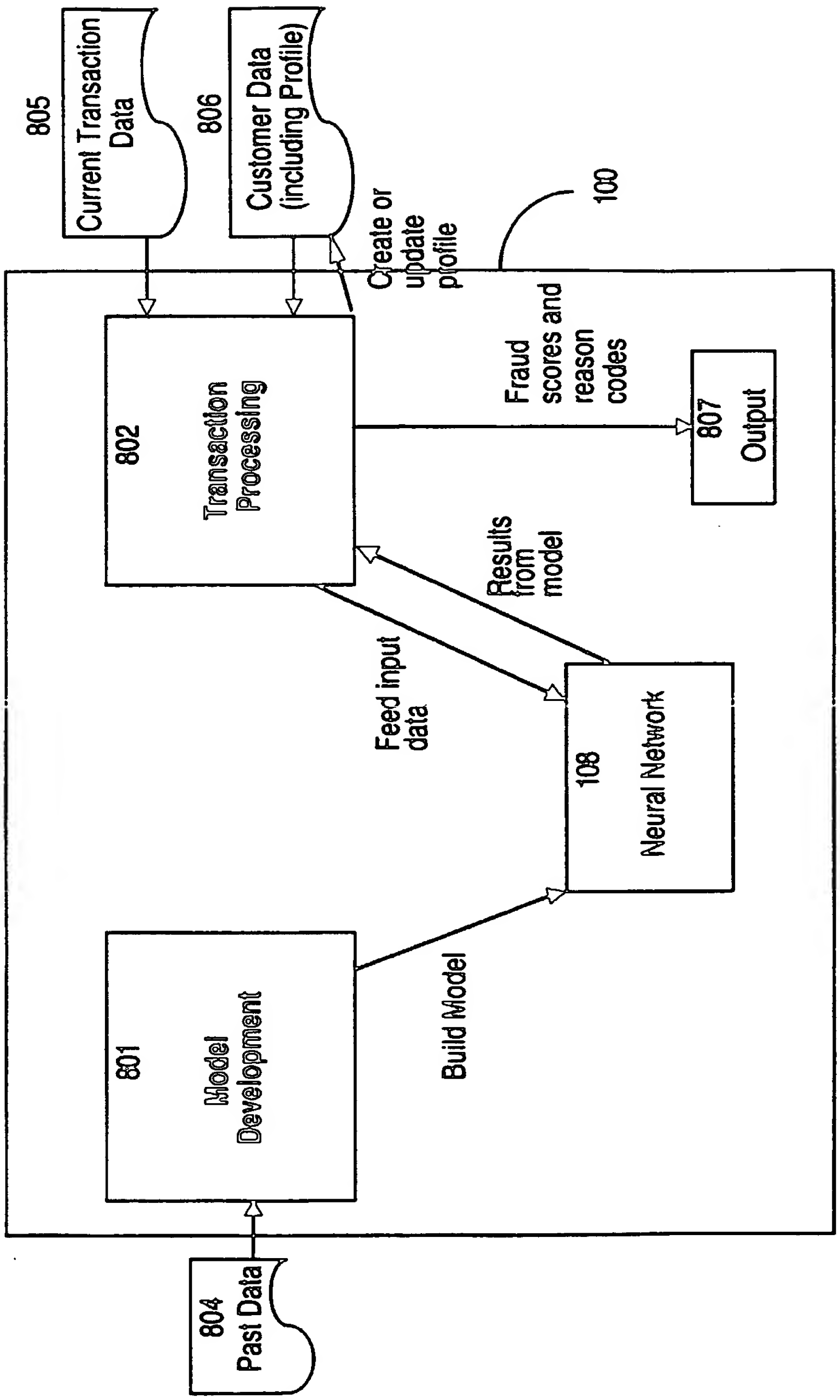

805
Current Transaction Data
806
Customer Data (including Profile)
100
Create or update profile
802
Transaction Processing
Fraud scores and reason codes
807
Output
Results from model
Feed input data
108
Neural Network
801
Model Development
Build Model
804
Past Data

FIGURE 8

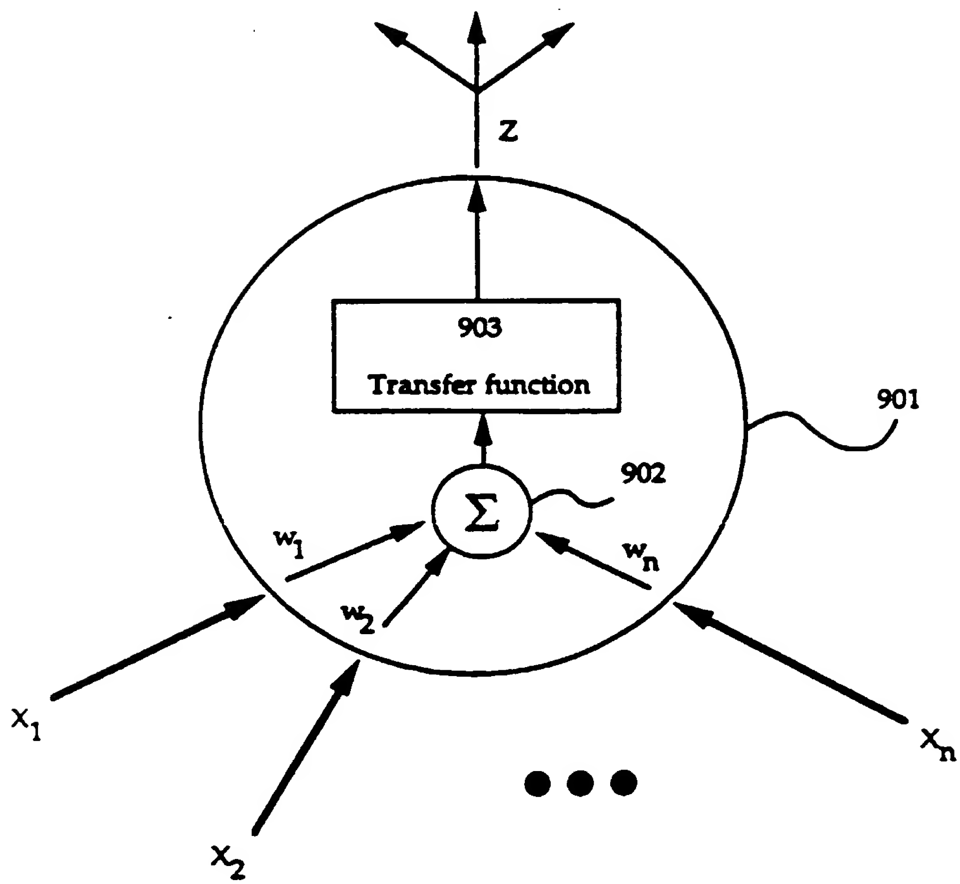


FIGURE 9

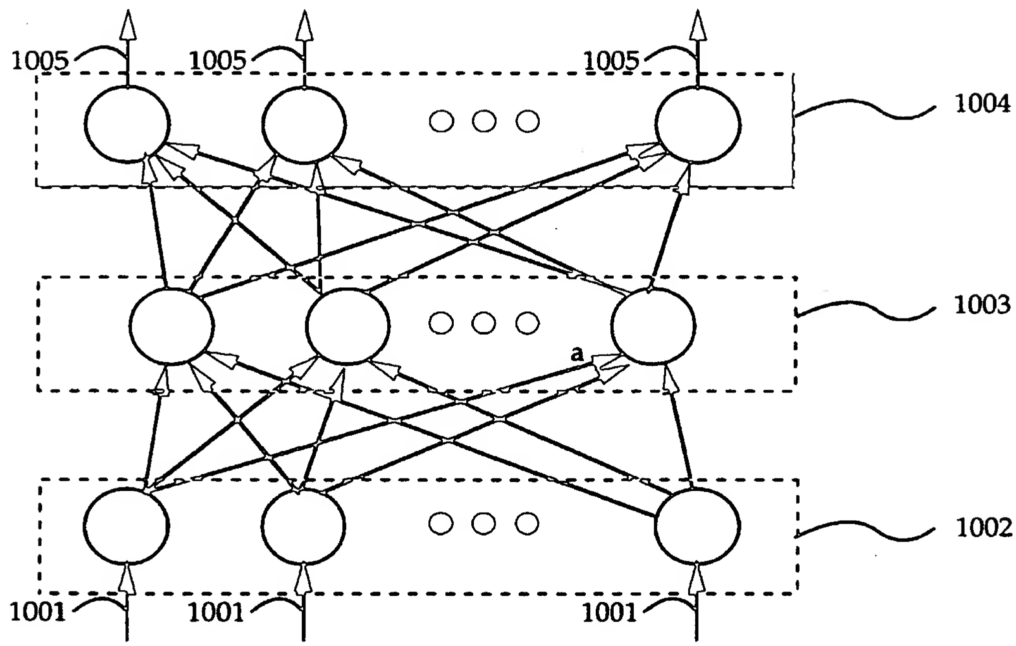


FIGURE 10

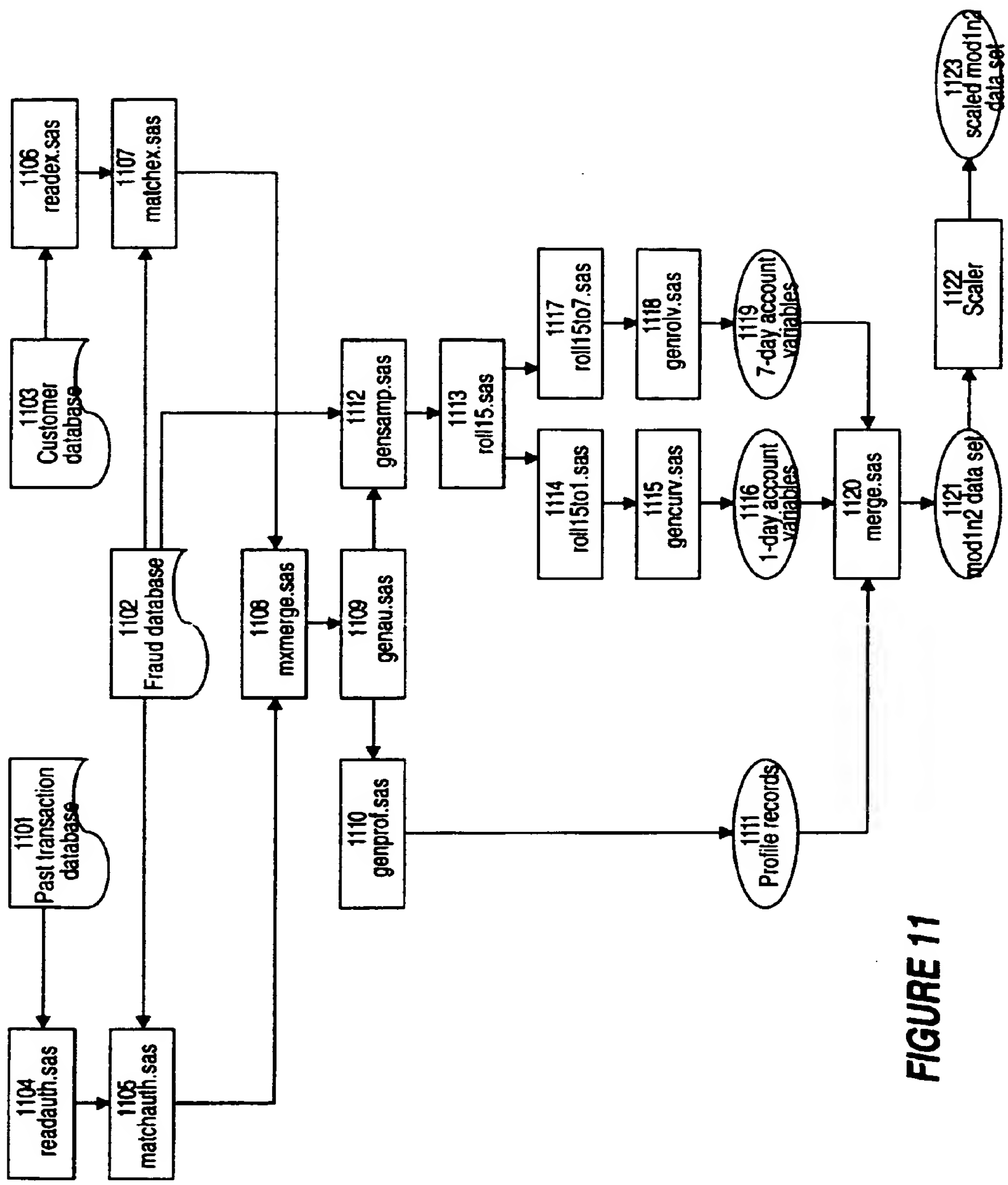

1101
Past transaction database
1102
Fraud database
1103
Customer database
1104
readauth.sas
1105
matchauth.sas
1106
readex.sas
1107
matchex.sas
1108
mxmerge.sas
1109
genau.sas
1110
genprof.sas
1111
Profile records
1112
gensamp.sas
1113
roll15.sas
1114
roll15to1.sas
1115
gencurv.sas
1116
1-day account variables
1117
roll15to7.sas
1118
genrolv.sas
1119
7-day account variables
1120
merge.sas
1121
mod1n2 data set
1122
Scaler
1123
scaled mod1n2 data set

FIGURE 11

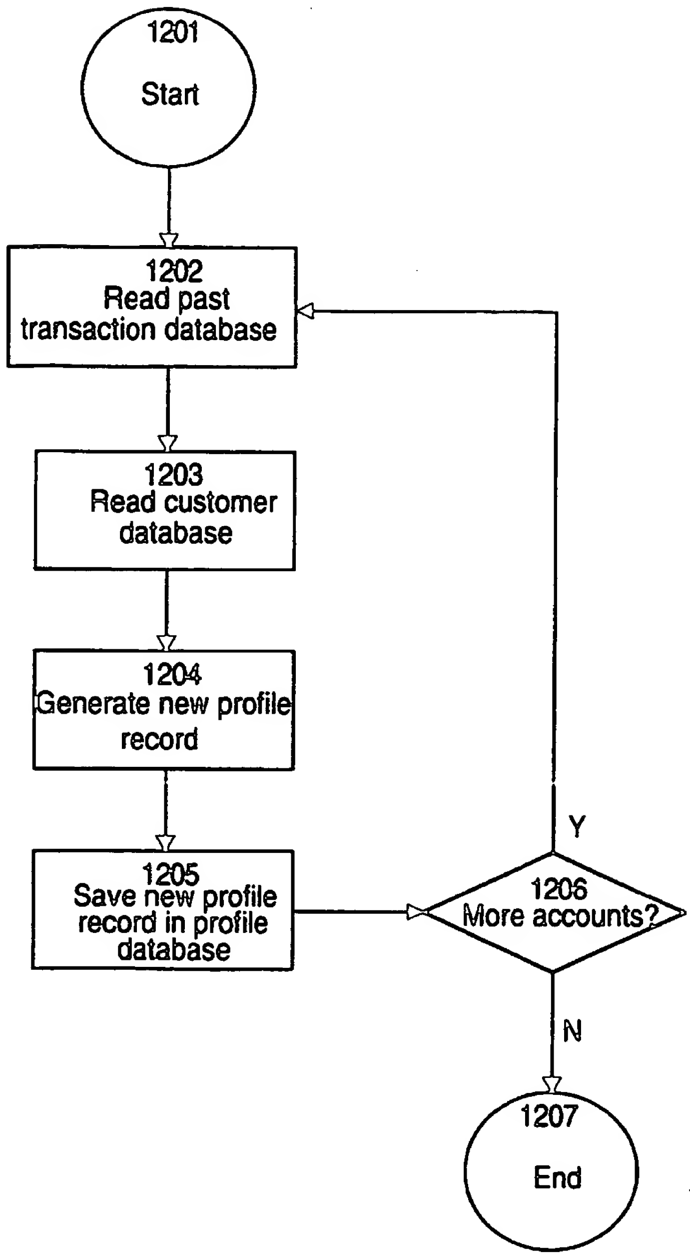

1201
Start
1202
Read past
transaction database
1203
Read customer
database
1204
Generate new profile
record
1205
Save new profile
record in profile
database
1206
More accounts?
Y
N
1207
End

FIGURE 12

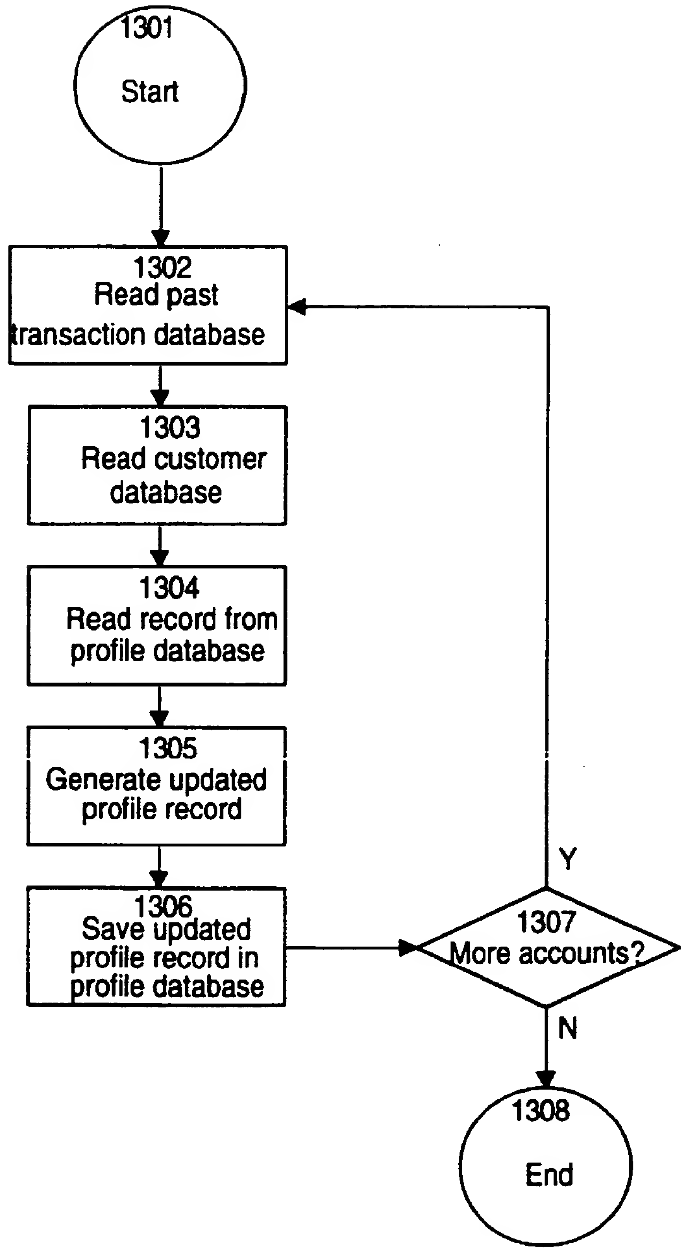

1301
Start
1302
Read past
transaction database
1303
Read customer
database
1304
Read record from
profile database
1305
Generate updated
profile record
1306
Save updated
profile record in
profile database
Y
1307
More accounts?
N
1308
End

FIGURE 13

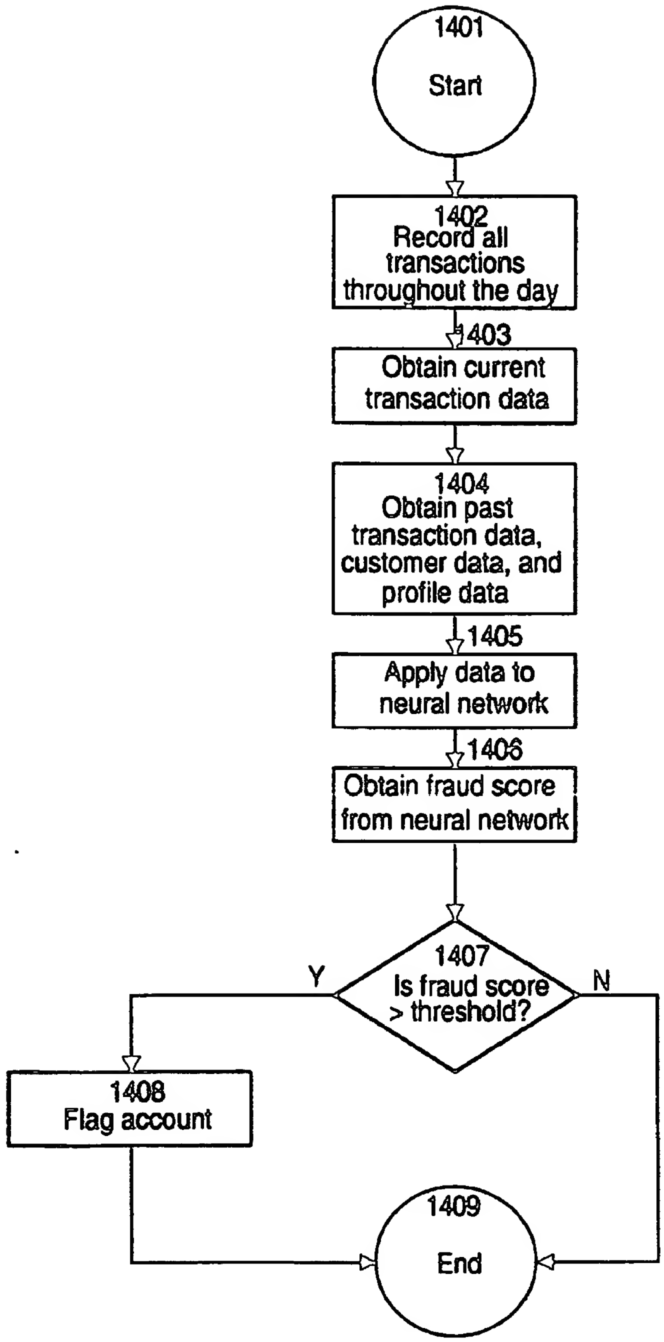

1401
Start
1402
Record all transactions throughout the day
1403
Obtain current transaction data
1404
Obtain past transaction data, customer data, and profile data
1405
Apply data to neural network
1406
Obtain fraud score from neural network
1407
Is fraud score > threshold?
Y
N
1408
Flag account
1409
End

FIGURE 14

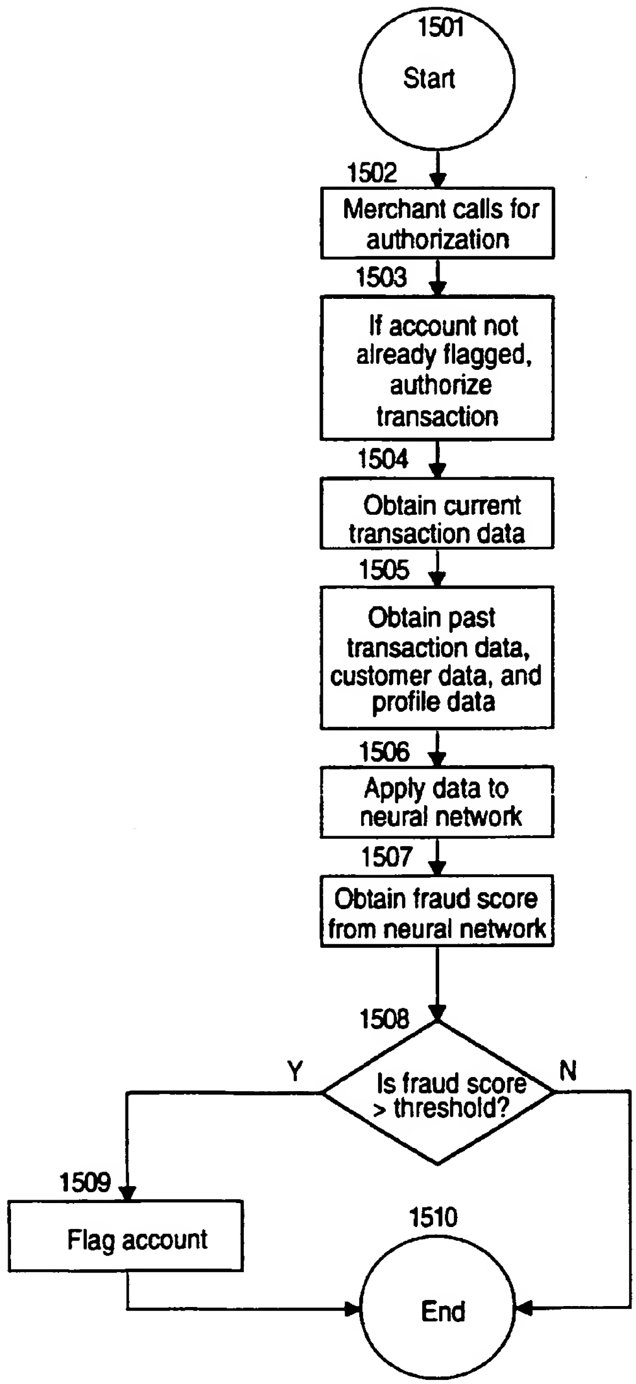

1501
Start
1502
Merchant calls for authorization
1503
If account not already flagged, authorize transaction
1504
Obtain current transaction data
1505
Obtain past transaction data, customer data, and profile data
1506
Apply data to neural network
1507
Obtain fraud score from neural network
1508
Is fraud score > threshold?
Y
N
1509
Flag account
1510
End

FIGURE 15

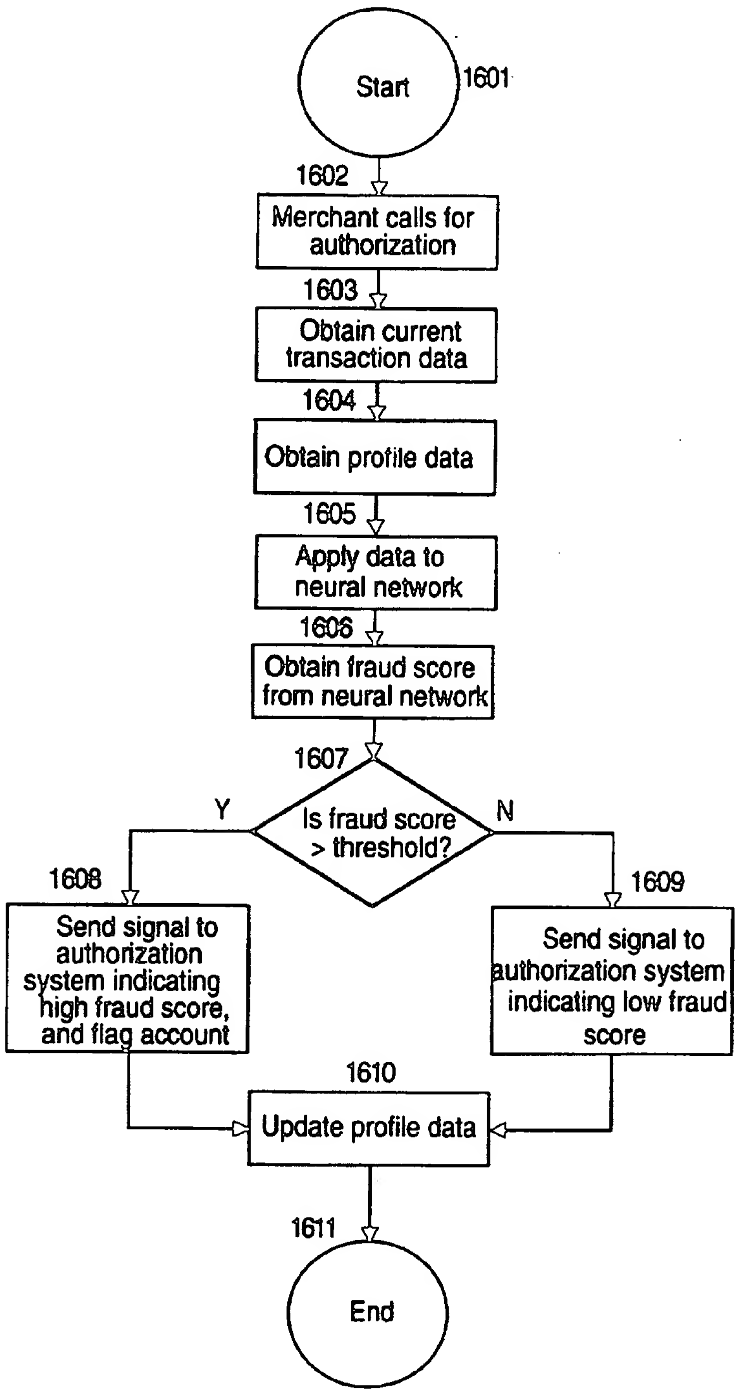

Start
1601
1602
Merchant calls for authorization
1603
Obtain current transaction data
1604
Obtain profile data
1605
Apply data to neural network
1606
Obtain fraud score from neural network
1607
Is fraud score > threshold?
Y
N
1608
Send signal to authorization system indicating high fraud score, and flag account
1609
Send signal to authorization system indicating low fraud score
1610
Update profile data
1611
End

FIGURE 16

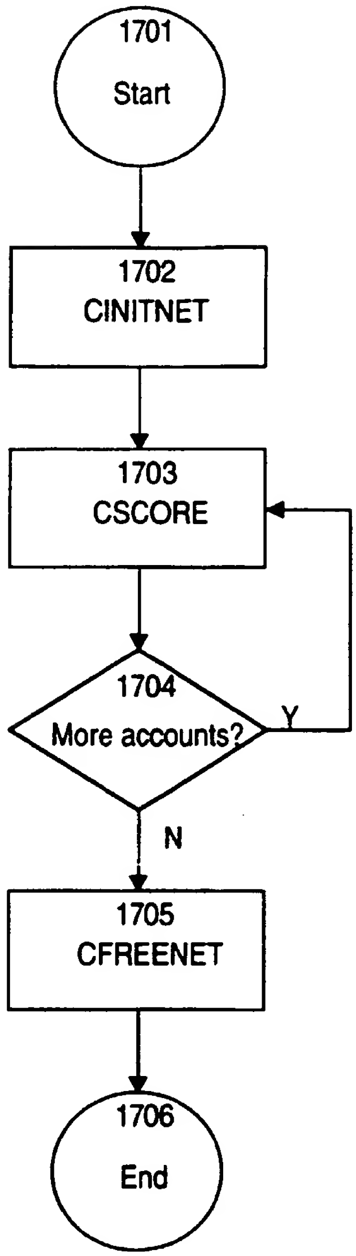

1701
Start
1702
CINITNET
1703
CSCORE
1704
More accounts?
Y
N
1705
CFREENET
1706
End

FIGURE 17

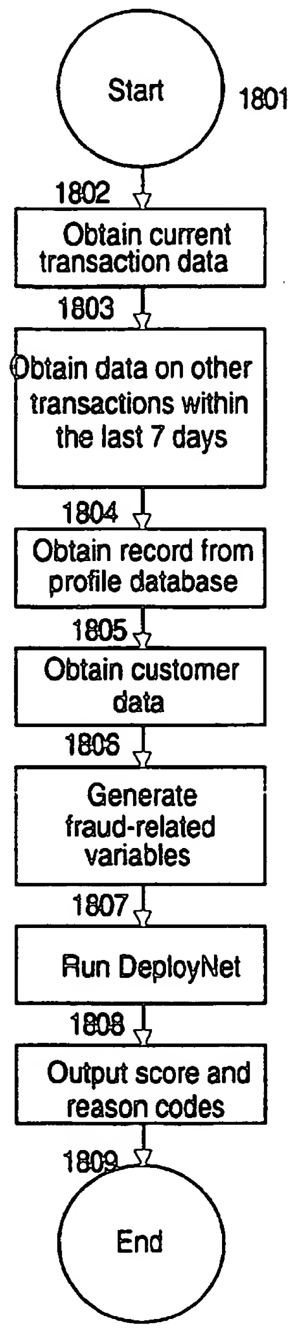

Start
1801
1802
Obtain current transaction data
1803
Obtain data on other transactions within the last 7 days
1804
Obtain record from profile database
1805
Obtain customer data
1806
Generate fraud-related variables
1807
Run DeployNet
1808
Output score and reason codes
1809
End

FIGURE 18

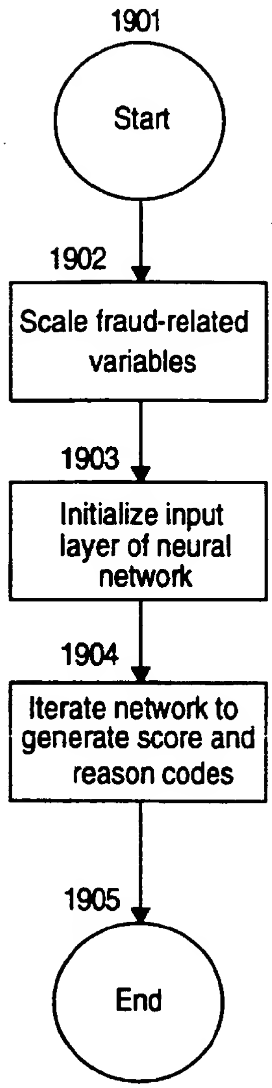

1901
Start
1902
Scale fraud-related variables
1903
Initialize input layer of neural network
1904
Iterate network to generate score and reason codes
1905
End

FIGURE 19

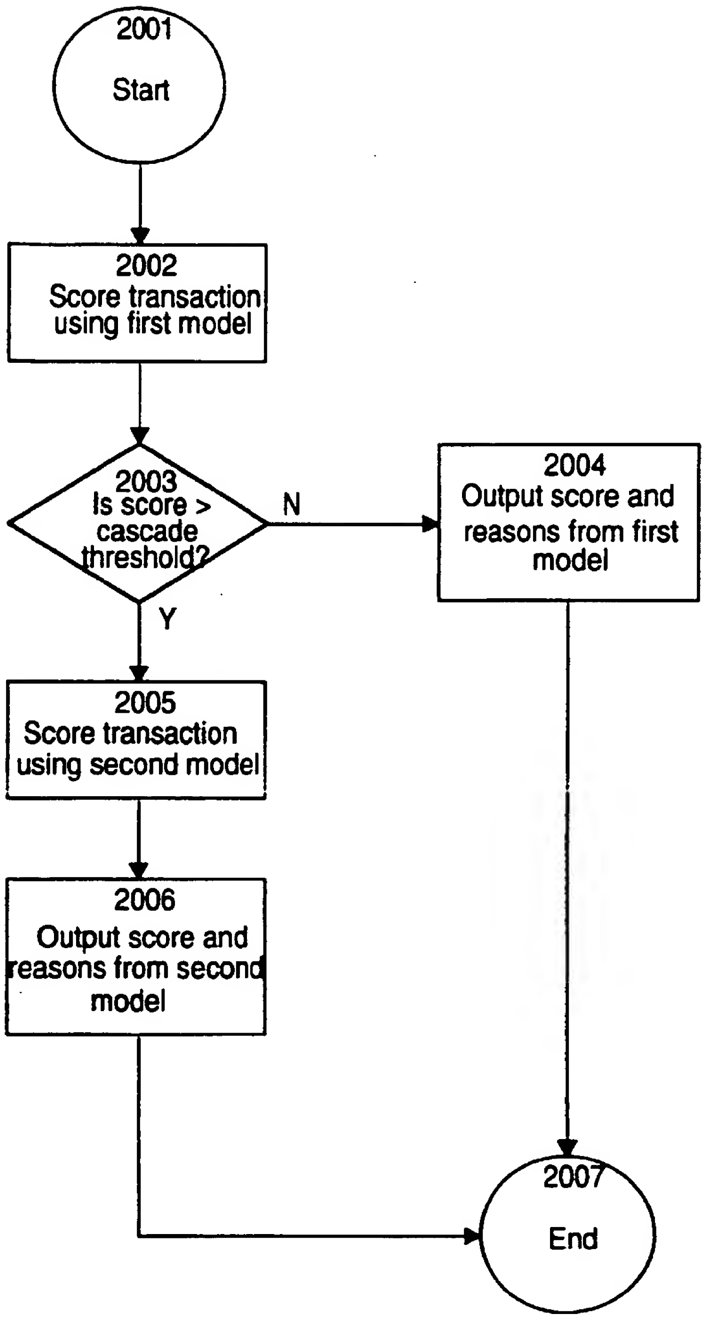

2001
Start
2002
Score transaction using first model
2003
Is score > cascade threshold?
N
Y
2004
Output score and reasons from first model
2005
Score transaction using second model
2006
Output score and reasons from second model
2007
End

FIGURE 20

Record Length=784

0
Name= ACCOUNT
Type=EXCLUDE
Slab=NONE
Size=0
Start=0 Length=16
RecCnt=0
Min=1.7976931e+308 Max=-1.7976931e+308
MissingValue=0.
Sum=0.
Mean=0.
StdDev=0.
Derivative=0 2101
TimeSlice=0
NbrOfSymbols=0
Symbolic=NUMERIC
ScaleMode=AUTO ScaleFn=LIN
DivFlag=0
Divisor=0. Range=0.

0
Name=PAUDYMDY
Type=CONTINUOUS
Slab=INPUT
Size=1
Start=16 Length=12
RecCnt=23312
Min=3.22581e-002 Max=1.
MissingValue=0.18761507
Sum=4373.6825 2102
Mean=0.18761507
StdDev=0.13174467
Derivative=0
TimeSlice=0
NbrOfSymbols=0
Symbolic=NUMERIC
ScaleMode=AUTO ScaleFn=LIN
DivFlag=0
Divisor=0. Range=0.9677419

FIGURE 21